Financial Development and Convergence Clubs*

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Abstract

This paper studies the economic development process, measured by Gross Domestic Product (GDP), for a large panel of countries. We propose a methodology that identifies groups of countries (convergence clubs) that show similar GDP structures, while allowing for changes in club memberships over time. As a second step we analyze the short-run and long-run effects of financial development (measured by financial intermediary development and stock market development) on the GDP process, and the composition of the convergence clubs. We find that the club memberships are quite persistent, but still their compositions change substantially over time. In particular, several EU member countries and East Asian countries are found to belong to a higher GDP club in recent times compared to the beginning of the 1970s. In terms of the effects of financial development indicators on the GDP process, our results partially confirm the theoretical basis for different effects of financial development indicators in the short-run and the long-run. In the long-run, financial development is found to affect the countries' GDP level positively. The short-run effects of financial development indicators however are found to be less clear, in the sense that we do not find a negative short-run effect of financial intermediary development on GDP levels, while the short-run effect of stock market development is found to be negative.

Keywords: *Economic Growth, Convergence Clubs, Financial Development, Markov Chain Models.*

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1 Introduction

Starting with neoclassical growth theory, it has been argued that the real per capita incomes of (subsets of) countries should converge in the long-run. Early empirical work studying the existence of income convergence, such as Barro (1991) and Mankiw and Romer (1992), investigates this issue using pure cross-sectional analysis. These studies examine the presence of convergence through the effect of initial income on the average real GDP per capita growth rates of countries over some long time period. Controlling for other variables, a negative coefficient on initial GDP implies that (relatively) poorer countries at the beginning of the sample period grow faster than richer countries. In return, such findings provide evidence for *conditional catch-up* given the rest of the covariates.

It is well documented that the pure cross-sectional analysis of convergence has severe pitfalls. The criticisms can be summarized by two main points. First, analyzing average GDP levels or growth rates over a long time period brings potential misspecification problems as this kind of data cannot uncover the time series dynamics of the GDP process (see e.g. Quah (1993) and Bernard and Durlauf (1995)). Second, these studies define convergence through the growth rates in GDP series. However, the main question in convergence is whether the poor countries will eventually catch up with the rich in real GDP per capita levels. The main focus should therefore be the gaps between GDP levels, instead of GDP *growth rates*, as convergence of the former is an implication of the catch-up process (see Quah (1993); Friedman (1992); Evans (1998) and Bianchi and Menegatti (2007) among many others).

Following these criticisms, several studies adopt a (panel) time series approach to analyze convergence. In general, these studies focus on the GDP per capita gaps between countries over time using cointegration techniques to analyze whether income disparities between countries are persistent (see e.g. Evans (1998) and Pesaran (2007)). As opposed to the earlier cross-sectional studies, time-series tests for convergence tend to find no support for convergence among all countries.

It is argued that the findings of the time-series studies stem from the properties of the world income distribution. The cross-country distribution of real GDP per capita is far from a unimodal distribution, hence assuming a single long-run GDP level for all countries is unrealistic. Some empirical studies find that sub-groups of countries show similar GDP patterns in the long-run, but this result cannot be generalized to all countries (see Ben-David (1994); Quah (1996) and Durlauf and Johnson (1995)). This evidence supports theories of *convergence clubs* (Baumol, 1986; Galor, 1996) in the sense that there is no global convergence, but rather groups of countries following similar GDP patterns. Furthermore, the time series in GDP levels show different forms of transitional behavior for countries. While some countries or economic regions are found to have similar GDP structures over time, other countries or regions show diverging GDP levels for certain periods of time, and catch-up in other time periods (Phillips and Sul, 2009).

More recent studies exogenously group countries, for instance based on regions, and test for convergence within these groups. Despite accounting for the time-series dynamics of the growth process, these studies cannot accommodate the possibility of changes in the composition of the convergence clubs over time, but can only test for the existence of convergence within the specified group of countries. For this reason, clustering based on mixture distributions and MCMC methods has recently drawn a lot of attention in the economic growth literature.

One of the main reasons for the popularity of mixture distributions is the possibility to analyze the distribution of countries over the poor and rich groups as well as the composition of the poor/rich groups over time. Paap and Van Dijk (1998); Bloom *et al.* (2003); Canova (2004); Paap *et al.* (2005) and Baştürk *et al.* (2008) use mixture distributions for this purpose. To our knowledge, neither the individual countries' movements between convergence clubs, nor the possible factors affecting these changes are analyzed in the existing studies.

The purpose of this chapter is hence to model the convergence process for a large set of countries in terms of GDP levels, accounting for changing intra-distributional dynamics. Specifically, we address three questions regarding the unconditional convergence process[1]. The first question we address is whether there are sub-groups of countries that follow the same long-run path in real GDP per capita levels. With respect to this question, we estimate models with different specifications, and consider the number of distinct groups within the data. Furthermore, instead of using exogenous factors, such as regions, to define club memberships, we determine the club memberships endogenously, using real GDP data only.

Our second question concerns the composition of these clubs. Most of the convergence literature does not deal with possible changes in the composition of these clubs. Our methodology explicitly allows countries to switch between GDP clubs over time. Hence, the composition of the clubs is not fixed over time. Furthermore, we analyze whether macroeconomic and financial variables that affect the probability of switching to a different cluster can be identified.

Our third question is whether the composition of these GDP clubs can be explained by initial conditions and financial development[2]. Empirical studies on the effect of financial development on growth are document contradicting results, see Loayza and Ranciere (2006). Both the theoretical and empirical literature on the link between financial development and convergence clubs suggest a positive long-run effect of financial development on growth coexisting with a general negative effect in the short-run (Levine, 2004; Beck, 2008).

The empirical studies analyzing the effect of financial development on growth focus either in the long-run or in the short-run. One exception is Loayza and Ranciere (2006) accounting for both the short-run and long-run effects of financial development on real GDP per capita growth rates. They propose an error-correction model where there is a single long-run relationship between financial development indi-

[1]Note that there is a distinction between the *conditional* and *unconditional* convergence in the literature. In this study, we adopt the exact definition of convergence, in the sense that long-run income levels converge within the endogenously determined clubs.

[2]Our model is general enough to specify different variables that affect the GDP levels in the short-run or in the long-run. However, following the discussion on the effects of financial development on growth, we especially focus on the conventional measures of financial development, namely measures of financial intermediary development and stock market development, on the formation of convergence clubs.

cators and growth. We follow their idea of incorporating possible short-run and long-run effects of financial development in the economic growth model. However, we do not assume a cointegrating relationship between financial development and growth. Instead, we define financial development indicators as factors that possibly affect the GDP club of a country in the long-run.

For the GDP club analysis, we propose a novel Markov Chain State Space Model that endogenously defines the groups of countries that show similar GDP structures. We model the common paths for the countries' real GDP levels and growth rates. We do not make stationarity assumptions for club memberships, but rather allow countries to switch between clubs over time. Our methodology provides a general analysis of convergence clubs. We do not specify an a priori group of countries that follows similar GDP structures, but rather extract the GDP behavior from the data.

In order to check whether financial development affects these club memberships in the short-run and the long-run, we extend the Markov switching specification allowing for covariates affecting the transition between GDP clubs, as well as defining covariates affecting the short-run fluctuations in GDP levels. The key point in this second model is the distinction between the short-run and long-run effects of financial development. We distinguish the short-run effects as factors affecting fluctuations around the common cluster levels. In the long-run however, financial development and the initial conditions are anticipated to explain the composition of the GDP clusters.

The models we propose are related to a wide range of studies focusing on convergence clubs, and studies employing methods for clustering the data in general. The long-run club formation we analyze is similar to the cointegration based methods, (Bernard and Durlauf, 1995; Pesaran, 2007). Our model generalizes these methods in the following way: we do not assume a single long-run relationship for the GDP series across countries, but rather allow for more than one convergence club for the included countries. Furthermore, we allow changes in the cluster memberships over time, indicating possible changes in the long-run GDP correlations of the included countries.

Specifically, a GDP club can have no member countries during a part of the sample period, indicating a merger between this club and one of the other clubs, depending on the changes on the club membership over time. Alternatively, the latent long-run GDP levels for some clusters can converge over time. Identifying the memberships for these clusters is harder, but the interpretation of the catching-up process holds: countries belonging to converging clusters have similar long-run GDP patterns. Note that the methodology we propose is more general compared to the beta and sigma convergence definitions in the literature, which analyze the existence of decreasing long-run trends in GDP and decreasing short-run fluctuations around the common long-run path, respectively.

Our methodology for clustering the data is related to studies proposing endogenous clustering techniques in order to cluster the GDP per capita of countries. In these specifications, one does not have to specify certain covariates defining the groups of countries. The classification rather depends on the data only. For example Paap and Van Dijk (1998); Paap *et al.* (2005); Baştürk *et al.* (2008) use Markov

Chain models and finite mixture models for this purpose. The models we propose are extensions of their work by clustering GDP levels directly, instead of GDP growth rates, as well as allowing for certain covariates to affect the changes in the club memberships and short-run GDP fluctuations.

In terms of the methodology, Frühwirth-Schnatter and Kaufmann (2008) and Hamilton and Owyang (2009) are the two papers closest to this paper. Both studies propose Markov Chain models to assess the subgroups of the data that show similar characteristics. They further allow for covariates to affect the group memberships. Our model builds on these models by modeling the time-dependent data characteristics. Incorporating the state space structure in the Markov Chain model, we estimate the common paths within the groups of data, while allowing for changes in the club compositions over time.

In order to estimate the model we pursue a Bayesian approach and use Gibbs Sampling (Geman and Geman, 1984). We find that the club memberships are quite persistent, but still group compositions change substantially over time. In particular, several EU member countries and East Asian countries are found to belong to a higher GDP club in recent times compared to the beginning of the 1970s. Regarding the effects of financial development indicators on the GDP process, our results confirm the theoretical basis for different effects of financial development indicators in the short-run and the long-run. In the long-run, financial development is found to affect the countries' GDP level positively. In the short-run however, we find that the effect of financial intermediary development on GDP levels are in general negative.

The remainder of this paper is as follows: Section 2 introduces the models for GDP club formation. Section 3 presents the Bayesian estimation method and the Gibbs Sampling scheme. Section 4 applies the proposed models on the real GDP per capita data. Section 5 concludes.

2 Model Specification

In this section we propose our modeling approach which aims to identify clusters of countries sharing a common growth path in their GDP per capita. Note that in the economic growth context, the term 'convergence clubs' is used for groups of countries with a common growth path. In the mixture models literature, the term 'cluster' is more common. In this paper we use the latter terminology in describing the model specification.

Let $y_{i,t}$ denote the log real GDP per capita of country $i = 1, \ldots, N$ at time $t = 1, \ldots, T$. We assume that there are J clusters of countries. Within each cluster countries have the same long-run growth path, while the growth paths may differ across clusters. We specify the stochastic growth path of the jth cluster as a random walk[3] with a constant cluster-specific drift β_j and variance $\sigma^2_{\nu,j}$:

$$\mu_{j,t} = \mu_{j,t-1} + \beta_j + \nu_{j,t}, \tag{1}$$

[3]Note that modeling annual log real GDP per capita series as a random walk process is the standard approach in the literature as most cross-sectional series for the annual log real GDP per capita are found to have one unit root only.

where $\nu_{j,t} \sim NID\left(0, \sigma^2_{\nu,j}\right)$ for $j = 1, \ldots, J$.

An important feature of our model is that the composition of the clusters need not be constant over time. Put differently, countries may switch between different clusters and hence may end up on a different long-run growth path. The latent variable $S_{i,t} \in \{1, \ldots, J\}$ is used to indicate which of the J clusters country i belongs to at time t. The real GDP per capita of country i at time t is described by

$$y_{i,t} = \left(\sum_{j=1}^{J} I[S_{i,t} = j] \mu_{j,t} \right) + x^s_{i,t} \psi^s + \varepsilon_{i,t}, \tag{2}$$

where $\varepsilon_{i,t} \sim NID\left(0, \sigma^2_i\right)$ and $I[.]$ is an indicator function taking the value of 1 if the argument is true, and 0 otherwise. The explanatory variables in $x^s_{i,t}$ together with the parameters ψ^s describe the country-specific short-run fluctuations of the individual GDP series around the common long-run growth path. $x^l_{i,t}$ in (2) may, for instance, include the degree of financial development or other macroeconomic and financial variables.

To complete the model, we have to specify the properties of the cluster membership, as represented by the latent variable $S_{i,t}$. In this paper we propose two different specifications. In the first specification we consider a first-order discrete Markov process for $S_{i,t}$ (see Hamilton (1994, Ch.22)). Let p_{kj} denote the probability that a country belonging to cluster k in period $t-1$ belongs to cluster j in period t, that is, $p_{kj} = \Pr\left(S_{i,t} = j \mid S_{i,t-1} = k\right)$ for $j, k \in \{1, \ldots, J\}$. In case of J clusters, these transition probabilities are collected in the matrix P,

$$P = \begin{bmatrix} p_{11} & & p_{1J} \\ & \ddots & \\ p_{J1} & & p_{JJ} \end{bmatrix}, \tag{3}$$

for all i, t. By definition, the Markov switching probabilities are such that $p_{kj} \in [0,1]$ for all k, j and $\sum_j p_{kj} = 1$ (see Hamilton (1994, p. 262)).

The first-order Markov specification for $S_{i,t}$ has the advantage that the clusters of countries sharing the same growth path are determined completely endogenously, only based on the GDP data, without any a priori grouping based on characteristics such as geographic location. On the other hand, it may be restrictive as transition probabilities are the same for all countries and constant over time. In the second specification we therefore relax both assumptions by relating cluster membership probabilities to certain explanatory variables. If we assume a clear ordering in the growth paths with respect to the explanatory variables, we can use an ordered probit model to describe segment membership:

$$\begin{aligned} S_{i,t} &= j \text{ iff } \left(\gamma_{j-1} < s^*_{i,t} \leq \gamma_j\right) \text{ for } j = 1, \ldots, J \\ s^*_{i,t} &= x^l_{i,t} \psi^l + \zeta_{i,t}, \end{aligned} \tag{4}$$

where γ_j for $j = 0, \ldots, J$ are threshold parameters with $\gamma_0 = -\infty$ and $\gamma_J = \infty$, and where $\zeta_{i,t} \sim \text{NID}\left(0, 1\right)$ with the variance of $\zeta_{i,t}$ fixed at 1 for identification. The parameter vector ψ^l describes the effect of the $x^l_{i,t}$ variable on the cluster membership and hence the long-run level and the growth rate for each observation. Positive values of these coefficients imply that the probability of a country to belong to a higher GDP cluster increases with the covariates. In our empirical analysis below, we include initial conditions and financial development indicators in the $x^l_{i,t}$ vector.

It is useful to note that there are several ways to relate the club membership to explanatory variables. Our choice for an ordered probit specification is motivated by the properties of the GDP data. First, a Markov process with time varying transition probabilities might seem a natural extension of the first specification above. Such a specification however requires a rather large number of observations to accurately identify and estimate the model parameters. Although we consider a large cross-section of countries, the number of time periods in our sample is quite restricted. Second, The ordered probit model provides a natural ranking in the GDP clubs. Other methods, such as a multinomial logit model for cluster memberships, does not provide such a ranking for the cluster levels, and solving the label switching problem in these models can be quite cumbersome (Frühwirth-Schnatter, 2006; Geweke, 2007)[4].

3 Estimation and Inference

We opt for a Bayesian approach to do inference in our proposed model. Specifically, posterior results for the model parameters and related statistics are obtained using Gibbs Sampling (Geman and Geman, 1984) together with data augmentation (Tanner and Wong, 1987).

To implement the Gibbs sampler, we first consider the complete data likelihood function of our model, which is given by

$$f(\mathcal{S};\vartheta)\prod_{i=1}^{N}\prod_{j=1}^{J}\prod_{t=1}^{T}\phi(\mu_{j,t};\mu_{j,t-1}+\beta_j,\sigma^2_{\nu,j})^{I[S_{i,t}=j]}$$
$$\phi(y_{i,t};\textstyle\sum_{j=1}^{J}I[S_{i,t}=j]\mu_{j,t}+x^s_{i,t}\psi^s,\sigma^2_i), \quad (5)$$

where $\phi(\cdot;\mu,\sigma^2)$ is the density function of a normal distribution with mean μ and variance σ^2 and $f(\mathcal{S};\vartheta)$ denotes the likelihood contribution of the model for the cluster membership variables summarized in $\mathcal{S}$ with parameter vector ϑ. For the Markov switching specification as given in (3) we have

$$f(S,\vartheta)\propto\prod_{j=1}^{J}\prod_{k=1}^{J}p_{kj}^{\mathcal{N}_{kj}}, \quad (6)$$

where $\mathcal{N}_{kj}$ denotes the number of transitions from cluster k to j and $\vartheta = P$. For the

[4]The label switching problem may occur since the model we propose does not define a ranking of groups such as clusters with low/high growth rates.

ordered probit specification (4) we have

$$f(S;\vartheta) \propto \prod_{i=1}^{N}\prod_{t=1}^{T}\prod_{j=1}^{J}\left(I[\gamma_{j-1} < s^*_{i,t} < \gamma_j]\phi(s^*_{i,t}; x^l_{i,t}\psi^l, 1)\right)^{I[S_{i,t}=j]} \tag{7}$$

with $\vartheta = \{\gamma_1, \ldots, \gamma_{J-1}, \psi^{(l)}\}$.

Regarding the priors, we consider conjugate or flat priors. More precisely, we use inverted Gamma priors for the variance parameters $\{\sigma^2_i\}_{i=1}^N$ and $\{\sigma^2_{\nu,j}\}_{j=1}^J$, flat priors for the parameters ψ^l, ψ^s, the cluster-specific drifts $\{\beta_j\}_{j=1}^J$ and the initial conditions $\{\mu_{0,j}\}_{j=1}^J$, Dirichlet priors for the transition probabilities in P and flat priors for the ordered probit parameters γ, taking into account the ordering in the parameters (i.e. $\gamma_k \leq \gamma_s$ for $k < s$).

For both specifications of $S_{i,t}$ our model is basically a (Markov) mixture State Space model. To obtain posterior results we can use the results of Carter and Kohn (1994) together with Frühwirth-Schnatter and Kaufmann (2008), except for updating the latent state variables (i.e. the cluster-specific growth paths $\mu_{j,t}$) and the cluster probabilities for the ordered probit model specification. To save notation we summarize the data by $\mathcal{Y} = \{\{y_{it}\}_{t=1}^T\}_{i=1}^N$. The sampling scheme is given by

(a) Given the cluster memberships and common growth paths, draw the model parameters:

- Draw $\{\sigma^2_{\nu,j}\}_{j=1}^J$ from $p(\sigma^2_{\nu,j} \mid \mathcal{Y}, \mathcal{S}, \{\mu_{j,t}\}_{t=0}^T, \psi^s, \vartheta, \{\sigma^2_i\}_{i=1}^N, \{\beta_j\}_{j=1}^J)$ for $j = 1, \ldots, J$ which are inverted Gamma distribution
- Draw $\{\sigma^2_i\}_{i=1}^N$ from $p(\sigma^2_i \mid \mathcal{Y}, \mathcal{S}, \{\mu_{j,t}\}_{t=0}^T, \psi^s, \vartheta, \{\sigma^2_{\nu,j}\}_{j=1}^J, \{\beta_j\}_{j=1}^J)$ for $i = 1, \ldots, N$ which are inverted Gamma distributions.
- Draw ψ^s from $p(\psi^s \mid \mathcal{Y}, \mathcal{S}, \{\mu_{j,t}\}_{t=0}^T, \vartheta, \{\sigma^2_{\nu,j}\}_{j=1}^J, \{\sigma^2_i\}_{i=1}^N, \{\beta_j\}_{j=1}^J)$ which is a normal distribution.

(b) Given the model parameters and cluster memberships, draw the latent state variables according to the underlying model:

- $\{\mu_{j,t}\}_{t=0}^T, \beta_j$ from $p(\{\mu_{j,t}\}_{t=0}^T, \beta_j \mid \mathcal{Y}, \mathcal{S}, \psi^s, \vartheta, \{\sigma^2_{\nu,j}\}_{j=1}^J, \{\sigma^2_i\}_{i=1}^N)$ for $j = 1, \ldots, J$ using the simulation smoother of Carter and Kohn (1994).

(c) Given the model parameters and the latent state variables, draw the cluster membership variables $\mathcal{S}$:

- Draw $\mathcal{S}$ from $p(\mathcal{S} \mid \mathcal{Y}, \{\mu_{j,t}\}_{t=0}^T, \psi^l, \vartheta, \{\sigma^2_{\nu,j}\}_{j=1}^J, \{\sigma^2_i\}_{i=1}^N, \{\beta_j\}_{j=1}^J)$. In case of a first-order Markov process model for the cluster memberships we can use the simulation smoother of (Albert and Chib, 1993a). For the ordered probit specification we can simply simulate the individual elements of $\mathcal{S}$ from multinomial distributions.

(d) The final steps of the Gibbs Sampling scheme concerns the simulation of the ϑ parameters.

- Draw ϑ from $p(\vartheta \mid \mathcal{Y}, \mathcal{S}, \{\{\mu_{j,t}\}_{t=0}^{T}\}_{j=1}^{J}, \psi^s, \{\sigma_{\nu,j}^2\}_{j=1}^{J}, \{\sigma_i^2\}_{i=1}^{N})$. In case we opt for a first order Markov mixture model, we can draw P from a Dirichlet distribution, see Koop (2003, p. 256)). For the ordered probit model specification on the other hand, we need to draw the ψ^l parameter, the latent variables $\mathcal{S}^* = \{\{s_{i,t}^{\star}\}_{t=1}^{T}\}_{i=1}^{N}$ and the probit thresholds $\gamma_1, \ldots, \gamma_{J-1}$ in (4), which can be done following Albert and Chib (1993b) and Koop (2003, p. 218).

The abovementioned Gibbs sampler is conditional on the number of clusters J. Following other frequentist and Bayesian studies in this area, we rely on information criteria for the choice of the number of clusters in the data. In the Bayesian context, most studies use the *Bayesian information criteria* (BIC) (Schwarz, 1978). It is however documented that in the missing data models or latent class models, the penalty for model complexity in the BIC criteria might not be satisfactory. Spiegelhalter *et al.* (2002) show this result in particular for hierarchical models, and propose *deviance information criteria* (DIC). For mixture models, Celeux *et al.* (2006) proposes extensions of the DIC. The main difference in interpretation between the BIC and DIC is the penalty for model complexity. Whereas the former explicitly accounts for the number of effective model parameters, DIC on the other hand considers the dispersion of the log-likelihood draws. Celeux *et al.* (2006) propose 8 different DIC specifications. We use the conditional DIC (*DIC7*) since this specification implicitly accounts for the latent variables as additional parameters. The BIC and DIC criteria are defined as:

$$
\begin{aligned}
BIC_J &= -2\tilde{l}_J(\theta) + \ln(N \times T) \times \kappa_J && (8)\\
DIC_J &= -4\bar{l}_J(\theta) + 2l_J(\bar{\theta}), && (9)
\end{aligned}
$$

where the vector θ contains the model parameters including the latent variables, κ_J is the number of parameters for the model with J clusters, and $l_J(\theta)$ is the log-likelihood function for the model with J clusters evaluated at θ. Furthermore, $l_J(\bar{\theta})$ is the log-likelihood function evaluated in the posterior mean, while $\bar{l}_J(\theta)$ and $\tilde{l}_J(\theta)$ are the mean and the maximum value of the log-likelihood over the draws.

4 Empirical Results

In this section we apply the convergence club model of Section 2 with the Markov switching specification (3) and the ordered probit model specification (4) to annual log real Gross Domestic Product per capita levels. We apply the model to two different data sets. In the first application we take a large cross-section of 163 countries but we do not consider covariates for the club memberships or short-run fluctuations. The reason for this decision is that our covariates of interest are available for a limited number of countries over a sufficiently long period of time. In the second application we consider a smaller set of 33 countries for which financial development indicators are available, in order to examine whether these are informative for the process of convergence club formation and short-run fluctuations in GDP.

In Section 4.1 we discuss the data sets in detail. Empirical results for the first and second applications are given in Section 4.2 and Section 4.3.

4.1 Data

The data for annual real GDP per capita are taken from the Penn World Tables (PWT), version 6.3, Heston *et al.* (2009). We consider the natural logarithm GDP, as percentage changes in GDP are more intuitive than the absolute changes.

In the first application we consider a balanced panel of 163 countries for the period 1970–2007. This data set is used to assess convergence club formation and changes in the composition of convergence clubs over time endogenously, without specifying certain covariates that affect the cluster membership probabilities or short-run GDP fluctuations. The countries in this data set are listed in Table 1.

Table 1: Markov switching specification (3): Included countries

Afghanistan, Albania, Algeria, Angola, Antigua and Barbuda, Argentina, Australia, Austria, Bahamas, Bangladesh, Barbados, Belgium, Belize, Benin, Bermuda, Bhutan, Bolivia, Botswana, Brazil, Brunei Darussalam, Bulgaria, Burkina Faso, Burundi, Cambodia, Cameroon, Canada, Cape Verde, Central African Republic, Chad, Chile, China, Channel Islands, Colombia, Comoros, Congo Dem. Rep., Congo Rep., Costa Rica, Côte d'Ivoire, Cuba, Cyprus, Denmark, Djibouti, Dominica, Dominican Republic, Ecuador, Egypt Arab Rep., El Salvador, Equatorial Guinea, Ethiopia, Fiji, Finland, France, Gabon, The Gambia, Germany, Ghana, Greece, Grenada, Guatemala, Guinea, Guinea-Bissau, Guyana, Haiti, Honduras, Hong Kong (China), Hungary, Iceland, India, Indonesia, Iran Islamic Rep., Iraq, Ireland, Israel, Italy, Jamaica, Japan, Jordan, Kenya, Kiribati, Korea Rep., Kuwait, Lao PDR, Lebanon, Lesotho, Liberia, Libya, Luxembourg, Macao (China), Madagascar, Malawi, Malaysia, Maldives, Mali, Malta, Marshall Islands, Mauritania, Mauritius, Mexico, Micronesia Fed. Sts., Mongolia, Morocco, Mozambique, Namibia, Nepal, Netherlands, New Zealand, Nicaragua, Niger, Nigeria, Norway, Oman, Pakistan, Palau, Panama, Papua New Guinea, Paraguay, Peru, Philippines, Poland, Portugal, Puerto Rico, Qatar, Romania, Rwanda, Samoa, São Tomé and Principe, Saudi Arabia, Senegal, Seychelles, Sierra Leone, Singapore, Solomon Islands, Somalia, South Africa, Spain, Sri Lanka, St. Kitts and Nevis, St. Lucia, St. Vincent and the Grenadines, Sudan, Suriname, Swaziland, Sweden, Switzerland, Syrian Arab Republic, Taiwan (China), Tanzania, Thailand, Togo, Tonga, Trinidad and Tobago, Tunisia, Turkey, Uganda, United Arab Emirates, United Kingdom, United States, Uruguay, Vanuatu, Venezuela RB, Vietnam, Zambia, Zimbabwe.

Note: The data consists of 163 countries for the period 1970–2007.

For the second application the data consists of annual real GDP per capita levels as well as financial development indicators. For this dataset, financial development indicators are taken as covariates possibly determining convergence club formation, and short-run GDP fluctuations of the individual series around the club-level.

The financial development indicators we consider can be classified into two main categories. The first category is labeled financial intermediary development, measured by Deposit Money Bank Assets as a percentage of GDP (*Bank assets*) and Commercial bank assets as a percentage of total assets (*Commercial/Central bank*). The second category is labeled stock market development, measured by stock market turnover (*turnover*). For more detailed descriptions of these financial development indicators, see Beck and Levine (2004); Rioja and Valev (2004); Aghion *et al.* (2005); Loayza and Ranciere (2006); Méon and Weill (2008). The data for financial development are taken from theBeck *et al.* (2000) database of financial development indicators, revised in May 2009.

The limited availability of the financial development indicators reduces both the time-series and the cross-sectional dimension of the data. For a balanced dataset including financial development indicators, our sample comprises 33 countries for the period 1989–2006. The countries included in this data set are listed in Table 2.

Table 2: Ordered probit model extension (4): Included countries

Argentina, Australia, Canada, Côte d'Ivoire, Chile, Denmark, Egypt, Finland, Greece, India, Indonesia, Israel, Italy, Jamaica, Japan, Jordan, Korea Rep., Malaysia, Morocco, New Zealand, Nigeria, Pakistan, Philippines, Portugal, Spain, Sri Lanka, Thailand, Trinidad and Tobago, Tunisia, Turkey, United Kingdom, United States.

Note: The data consists of 33 countries for the period 1989–2006.

As discussed in the introduction, financial development may have both short-run and long-run effects on GDP, albeit in opposite directions. In order to improve the identification of these short- and long-run effects, we consider different transformations of the financial development indicators. Specifically, we include lagged 5-year moving averages of the financial development indicators in the vector x_t^l, affecting the cluster probabilities in the ordered probit specification in (4). For the short-run variables, on the other hand, we use the one-year lagged financial development indicator in deviation from its 5-year moving average. Finally, in order to control for the effect of initial conditions on club memberships, we include the starting level of GDP per capita as an additional variable in x_t^l.

Note that the sample size substantially decreases when we include the financial development indicators, due to missing values in these variables. We could keep the sample size larger if we adopted a method to handle missing data, such as the Expectation Maximization algorithm. These methods however assume that the data are missing at random, which may not be appropriate for the financial development indicators, which have missing values for consecutive time periods rather than at random time points. Dealing with missing data in this case means that we have to assume a statistical model for the financial indictor variables. Due to the large number of missing observations, the results may depend strongly on the proposed method for dealing with missing data. Therefore, we do not pursue this approach and we choose to limit the sample size according to data availability. Both the cross-sectional and the time-series dimensions of the data are important for parameter estimation. Extracting the growth paths relies on the time series dimension of the data. On the other hand, the cross-sectional dimension of the data is necessary for a comparative analysis of the convergence clubs. For this reason, the choice for the number of countries and the time period in the above datasets is based on achieving a reasonable number of observations in both dimensions.

4.2 Endogenous formation of convergence clubs

We first apply the model in (2) to annual log real GDP per capita for 163 countries for the period 1970-2007. The purpose of this analysis is to analyze the formation of convergence clubs and the dynamics of their composition endogenously. For this reason we use the Markov switching specification in (3) for the club membership variable $S_{i,t}$, hence not specifying factors that may affect the club membership probabilities. Furthermore, we do not consider the effects of covariates for the short-run fluctuations in GDP, that is, we impose $\psi^s = 0$ in (2).

The proper priors for error variances and transition probabilities are defined as follows: Error variances for the latent GDP levels in each club $\{\sigma^2_{\nu,j}\}_{j=1}^J$, and country-specific error variances $\{\sigma_i^2\}_{i=1}^N$ have inverted Gamma priors. For the former, we divide the GDP series into J groups, where observations belonging to each group is determined by J quantiles of the GDP distribution in each period. For each group, we then set the mean of the inverted Gamma density equal to the estimated variance of within-group growth rates. The scale parameter is fixed at 5 to allow for a relatively large prior variance on the error variances. For $\{\sigma_i^2\}_{i=1}^N$, we use an inverted Gamma density with mean equal to the estimated variances of GDP within each country, and scale parameter set equal to 50. The Dirichlet priors for the transition probabilities P are defined as $\text{Dir}(x)$, where $x = 2 \times \imath$ and $\imath$ is the $1 \times J$ vector of ones [5].

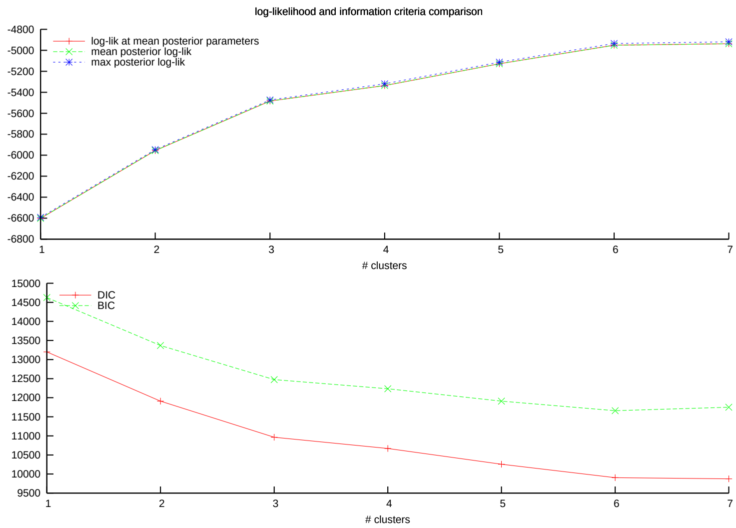
An important aspect of the analysis is to determine the number of convergence clubs in the data. The common practice in previous literature is to employ two to four GDP clubs (see e.g. Hansen (2000); Canova (2004); Paap *et al.* (2005)). Here we estimate models with two to seven clubs, as well as a single club model (which implies a pooled regression for all included countries) and use the information criteria (BIC and DIC) summarized in Section 3 to determine the appropriate number of convergence clubs.

The BIC and DIC comparisons for the different models are given in Figure 1, together with posterior log-likelihood summaries. Notice that posterior log-likelihood values at mean posterior parameters, mean posterior log-likelihood values, and maximum posterior log-likelihood values are almost the same in all cases. Both information criteria decrease with the number of clubs. This stems from the fact that the model we propose has a relatively small number of parameters compared to the number of unobserved variables, i.e. the long-run growth paths $\{\mu_{j,t}\}_{t=0}^T$ for $j = 1, \ldots, J$ and the club membership variable $S_{i,t}$. These latent variables, which bring additional uncertainty to the estimates, are not explicitly accounted for in both information criteria. In the literature, it is shown that DIC performs relatively better in mixture models, as it accounts for the model complexity through the deviance in the pos-

[5] The results are insensitive to small changes in the prior specifications. Furthermore, the posterior results for the variance terms are quite different from the prior means.

terior log-likelihood values. For the mixture model with latent variables we employ here, we cannot confirm this finding [6].

Figure 1: Markov switching specification (3): Posterior log-likelihood summary and Information Criteria Comparisons



Note: The figure shows posterior results for the first-order Markov switching specifications with 1 to 7 clubs, for the dataset with 163 countries. The top figure shows the posterior conditional log likelihood summaries: log-likelihood values at mean posterior parameters, mean posterior log-likelihood values, and maximum posterior log-likelihood values. The bottom graph shows BIC and DIC values.

Comparing BIC and DIC values, we confirm that the DIC penalty for model complexity, which depends on the posterior likelihood dispersion, is relatively higher. Despite this result, both information criteria do not provide sufficient penalty for model complexity for this model. Therefore we consider the differences in information criteria and posterior log-likelihood values for different numbers of clubs.

Figure 1 shows that the declines in the value of the information criteria become much smaller when more than three clubs are included in the model. The same result holds for the posterior log-likelihood summaries reported in Figure 1. We therefore choose the model with three clubs as our base model.

Table 3 shows posterior means for the transition probabilities in the model with three convergence clubs. The diagonal elements of the transition matrix are quite close to unity, indicating strong persistence in club membership. This is not a surprising result in the sense that shifts in long-run GDP growth paths by definition are

[6] Other criteria for model comparison, such as AIC, AIC3, and CAIC using posterior mode values of the log-likelihood lead to similar results. In particular, AIC3 and CAIC indicate the presence of five convergence clubs. However, the criteria values for the models with three and four clubs are quite close. Furthermore, estimating a model with five clubs leads to three clubs with very similar GDP growth paths.

not expected to occur frequently. Furthermore, there are no sudden shifts of countries from the low GDP club to the high GDP club, or vice versa, as the transition probabilities between these clubs are almost equal to zero.

Table 3: Posterior mean of the transition probability matrix

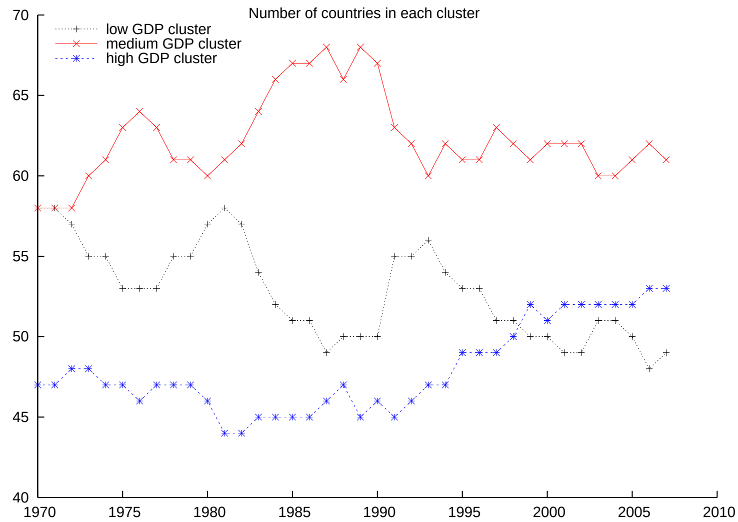
	Low GDP	Medium GDP	High GDP
Low GDP	0.98	0.01	0.00
Medium GDP	0.02	0.98	0.01
High GDP	0.00	0.01	0.99

Note: The table presents posterior mean of P in (3) for the dataset with 163 countries (1970–2007) without covariates. Clubs *high GDP*, *medium GDP*, and *low GDP* are labeled according to posterior mean of GDP levels ($\mu_{j,t}$) in the last period.

We emphasize, however, that the observed persistence in the transition probability matrix does not imply that countries never change from one convergence club to another. Instead, the near-identity transition probability matrix implies occasional changes in convergence club memberships. For example, it may be the case that a small number of countries that belong to the low GDP club during the beginning of the sample period switch at some point in time to the medium GDP club for the rest of the sample period. Although this results in a low off-diagonal transition probability, it is important to pinpoint this change in the club membership as it implies a structural change for these specific countries. Therefore we provide a more detailed analysis of cluster compositions for this model.

Figure 2 shows the number of countries in each club over the sample period, where we assign a country to a club based on the posterior mode value of $S_{i,t}$. We find that the composition of clubs clearly changes over time, despite the persistence of the Markov process. Two patterns stand out from the graph. First, until 1990 the number of countries in the high GDP club remains fairly constant, but a substantial number of countries switch between the low and medium GDP clubs. For example, the number of countries in the medium GDP club ranges between 58 in 1970-2 and 68 in 1987. Second, after 1990 the number of countries in the lowest GDP club steadily declines from 56 to 48, while the number of countries in the high GDP club increases from 45 to 52. The number of countries in the medium GDP clubs remains approximately constant during the second half of the sample period. Given that direct transitions from the low to high GDP club (almost) do not occur, this implies substantial changes in the composition of the medium GDP club, with some countries entering this group from the low GDP club and other countries exiting to the high GDP club. Also note that this result is in line with the arguments on changing intra-distributional dynamics, noted by Quah (1996), for instance. Quah (1996) argues that the world income distribution is subject to changes with the middle income class disappearing. Our results also indicate changes in the cross-sectional GDP distribution over time, but the changes are rather caused by the decrease in the number of countries belonging to the *low GDP* club rather than a disappearing middle income class.

Figure 2: Markov switching specification (3): Number of countries in each club over time



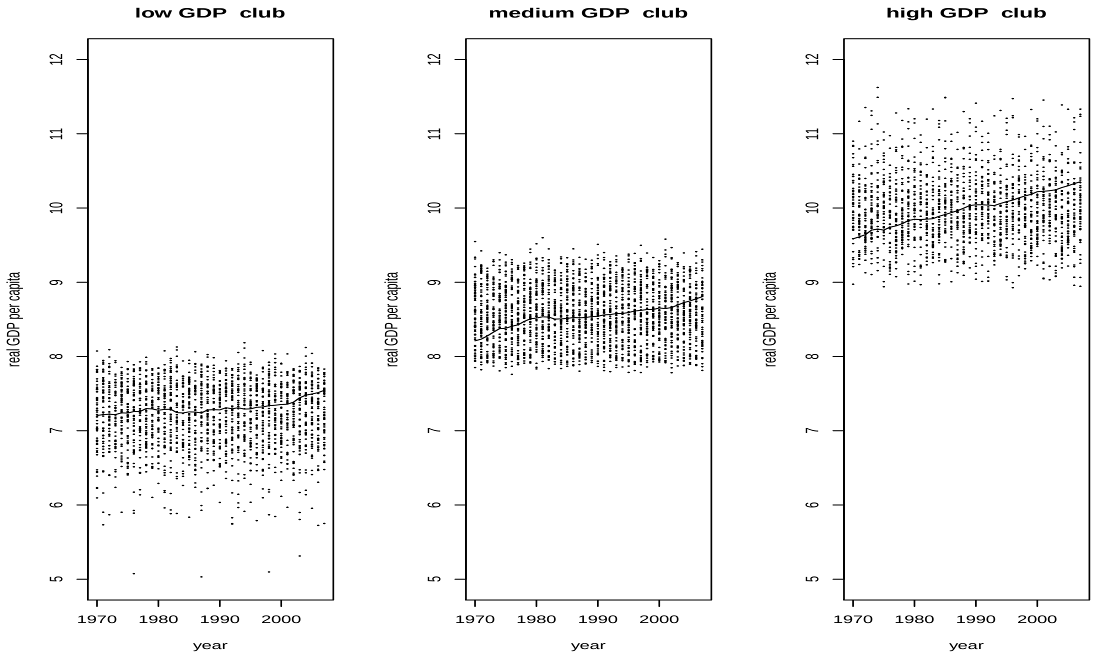
Note: The figure shows the number of countries in each club over the sample period for the three club model, for the dataset with 163 countries. Clubs *high GDP*, *medium GDP*, and *low GDP* are labeled according to posterior mean of GDP levels ($\mu_{j,t}$) in the last period. Club membership is determined by the posterior mode of the $S_{i,t}$ variable with a Markov switching specification.

Club-specific GDP paths and observations belonging to each club are shown in Figure 3. It can be seen that GDP levels and trends are quite different across clubs. We show these differences in detail in Table 4, reporting the initial GDP levels, growth rates and variances of GDP for each club.

Table 4 shows that initial GDP levels are clearly different across clubs, both in terms of the posterior mean and the reported percentiles. Mean annual growth rates for the *high GDP* and *medium GDP* clubs are both around 2%. The *low GDP* club on the other hand has a much lower growth rate. These results do not indicate convergence between clubs. First, the low GDP club starts with a relatively low GDP level, and the growth rate in this club is much lower than the other clubs. Hence we find that the low GDP club rather diverges from the rest of the convergence clubs. Second, although growth rates in the medium and high GDP club are very close, these clubs do not converge to a common level as a result of the substantial difference in initial conditions. Table 4 also shows variations in GDP values in each club. These values are quite similar across samples, hence the division of convergence clubs is not related to the club-specific GDP fluctuations.

We next report club memberships for each country. Table 5 reports the countries that stay in the same club over the sample period. Table 6 on the other hand reports the countries that change clubs at least once during the sample period. It can be

Figure 3: Markov switching specification (3): Club Memberships



Note: The figure shows the mean posterior club levels (lines), and mean posterior club memberships (symbols), for the dataset with 163 countries. Clubs *high GDP*, *medium GDP*, and *low GDP* are labeled according to posterior mean of GDP levels ($\mu_{j,t}$) in the last period. Club membership is determined by the posterior mode of the $S_{i,t}$ variable with a Markov switching specification.

Table 4: Markov switching specification (3): Initial GDP levels, growth rates and error variances for each club

	Club specification		
	low GDP	medium GDP	high GDP
GDP level $\mu_{j,t}$ in 1970	7.21	8.21	9.59
	(7.19, 7.22)	(8.20, 8.22)	(9.57, 9.60)
Growth rate β_j	0.006	0.021	0.023
	(0.002, 0.012)	(0.014, 0.040)	(0.020, 0.036)
Error variances $\sigma^2_{\nu,j}$	0.039	0.038	0.038
	(0.027, 0.059)	(0.027, 0.058)	(0.025, 0.055)

Note: The table shows posterior means for initial GDP levels ($\mu_{j,1970}$), growth rates (β_j) and error variances ($\sigma^2_{\nu,j}$) for each club, for the Markov switching specification. 2.5% and 97.5% percentiles of the posterior densities are reported in parentheses. Clubs *high GDP*, *medium GDP*, and *low GDP* are labeled according to posterior mean of GDP levels ($\mu_{j,t}$) in the last period.

seen that this is the case for around one third of the countries.

Table 5: Markov switching specification (3): Countries that do not change clubs over time

Low GDP club:
Afghanistan, Bangladesh, Benin, Burkina Faso, Burundi, Cambodia, Central African Rep., Chad, Comoros, Congo Dem. Rep., Ethiopia, Gambia, The Ghana, Guinea-Bissau, Haiti, Kenya, Lao PDR, Lesotho, Liberia, Madagascar, Malawi, Mali, Mauritania, Mozambique, Nepal, Niger, Nigeria, Pakistan, Papua New Guinea, Rwanda, Senegal, Solomon Islands, Somalia, Sudan, Syria, Tanzania, Togo, Uganda.
Medium GDP club:
Algeria, Belize, Bolivia, Brazil, Bulgaria, Colombia, Costa Rica, Cuba, Dominican Rep., Ecuador, El Salvador, Fiji, Guatemala, Honduras, Jordan, Marshall Islands, Mexico, Morocco, Namibia, Panama, Paraguay, Peru, Philippines, Poland, Romania, Samoa, São Tomé and Principe, South Africa, St. Lucia, Swaziland, Tonga, Tunisia, Turkey, Uruguay, Vanuatu.
High GDP club:
Australia, Austria, Bahamas, Barbados, Belgium, Bermuda, Brunei, Darussalam, Canada, Denmark, Finland, France, Germany, Greece, Hong Kong, Iceland, Ireland, Israel, Italy, Japan, Kuwait, Libya, Luxembourg, Macao, Netherlands, New Zealand, Norway, Palau, Portugal, Puerto Rico, Qatar, Saudi Arabia, Spain, Sweden, Switzerland, United Arab Emirates, United Kingdom, United States.

Note: The table presents the countries that stay in the same convergence club over the whole sample period (1970-2007). Clubs *high GDP*, *medium GDP*, and *low GDP* are labeled according to posterior mean of GDP levels ($\mu_{j,t}$) in the last period. Club membership is determined by the posterior mode of the $S_{i,t}$ variable with a Markov switching specification.

According to Tables 5 and 6, most sub-Saharan African countries in the sample are in the low GDP club throughout the entire sample period. Latin American countries are in general in the medium GDP club. Oil producing countries, are in the high GDP club throughout the sample period, with the exception of Oman, which temporarily switches to the medium GDP club in the year 1973.

Table 7 depicts a selection of countries that change clubs during the sample period together with the year in which the change took place. In particular, the model shows that several Asian countries (*Asian tigers*) switched to a higher GDP club compared to their initial club membership. Furthermore, some EU member countries, such as Cyprus, Hungary and Malta switched to the high GDP club.

In sum, we conclude that there are three separate clubs of countries in terms of the common GDP paths. The changing number of countries in each club, together with the differences in mean club levels, suggests that it is interesting to analyze the GDP clubs with a model which explains changes in club memberships over time. In Section 4.3 we analyze the effects of financial development indicators on the formation of GDP clubs and the dynamics of their composition.

Table 6: Markov switching specification (3): Countries that change clubs over the sample period

Albania, Angola, Antigua and Barbuda, Argentina, Bhutan, Botswana, Cameroon, Cape Verde, Chile, China, Channel Islands, Congo Rep., Côte d'Ivoire, Cyprus, Djibouti, Dominica, Egypt Arab Rep., Equatorial Guinea, Gabon, Grenada, Guinea, Guyana, Hungary, India, Indonesia, Iran Islamic Rep., Iraq, Jamaica, Kiribati, Korea Rep., Lebanon, Malaysia, Maldives, Malta, Mauritius, Micronesia Fed. Sts., Mongolia, Nicaragua, Oman, Seychelles, Sierra Leone, Singapore, Sri Lanka, St. Kitts and Nevis, St. Vincent and the Grenadines, Suriname, Taiwan, China, Thailand, Trinidad and Tobago, Venezuela, Vietnam, Zambia, Zimbabwe.

Note: The table presents the countries that change clubs at least once during the sample period (1970-2007). Club membership is determined by the posterior mode of the $S_{i,t}$ variable with a Markov switching specification.

Table 7: Markov switching specification (3): Selected countries and the time periods they change clubs

Previous club \ New club	Low GDP	Medium GDP	High GDP
Low GDP		Bhutan (2001) Botswana (1976) China (1995) Egypt (1983) India (2006) Indonesia (1987) Thailand (1977) Vietnam (2006)	
Medium GDP	Zambia (1976) Zimbabwe (2003)		Chile (1995) Cyprus (1982) Hungary[a](1999) Korea, Rep (1990) Malaysia (1995) Malta (1986) Singapore (1982) Taiwan (1987)
High GDP		Iran (1978) Lebanon[a](1988) Venezuela (1989)	

Note: The table summarizes selected countries' club changes over time, for the Markov switching specification, dataset with 163 countries for the period between 1970–2007. The year of change is indicated in parentheses. Clubs *high GDP*, *medium GDP*, and *low GDP* are labeled according to posterior mean of GDP levels ($\mu_{j,t}$) in the last period. Club membership is determined by the posterior mode of the $S_{i,t}$ variable with a Markov switching specification.

[a] denotes the countries that change clubs more than once. For these countries we report the year after which the country stays in the same club.

4.3 Effects of financial intermediary development and stock market development on convergence clubs

The purpose of this section is to analyze whether initial conditions and financial development indicators have explanatory power for the long-run GDP growth paths (in terms of club membership probabilities) as well as the short-run deviations from these. The dataset concerns a balanced panel of 33 countries for the period 1989-2006, and includes log real GDP levels, financial intermediary development and stock market development indicators as explained in Section 4.1. Priors for the error variances and transition probabilities in (1) and (2) are defined as in Section 4.2[7].

We consider the ordered probit specification (4), using financial development indicators as long-run and short-run factors affecting GDP club membership probabilities and short-run deviations from the club levels, respectively. We focus on the two club model for a number of reasons. First, most countries included in the smaller dataset belong to either the medium or high GDP club in the analysis in Section 4.2. Second, for more than three clubs, we found that at least one of the clubs systematically disappeared, with no observations belonging to the club. Third, the results for three clubs were quite sensitive to the included countries. Finally, we examined the robustness of the results by repeating the estimation 33 times, where one of the countries was removed from the dataset in turn. This analysis shows that the estimation results of the two-club model are quite robust. For the three-club model on the other hand, both GDP levels within clubs and the marginal effects of the covariates vary substantially depending on the composition of the panel. Therefore, in the remainder of this section, we focus on the two-club model.

Table 8 shows club membersips for the two club model. Similar to the model employed in Section 4.2, club memberships seem to be persistent as most countries do not change clubs over time. Still we find that 15% of the countries change clubs at some point during the sample period. Note that the number of years in this dataset is quite small compared to that of Section 4.2, which explains the smaller percentage of countries changing clubs over time[8].

Club-specific GDP paths and the observations belonging to each club are shown in Figure 4. GDP levels are quite different across clubs. Specifically, the high GDP club has a relatively high initial GDP level and the club levels do not seem to converge at the end of the sample period. This difference is shown in detail in Table 9, where we report initial GDP levels, GDP growth rates and the error variances for each club.

Table 9 shows that the mean GDP growth rates are the same across clubs. Together with this finding, the difference in initial GDP levels implies a persisting difference in the GDP levels across clubs. Hence for this dataset, we conclude that there is no indication of convergence (or divergence) across clubs. The GDP clubs are rather defined in terms of two separate paths with similar growth rates, but dif-

[7]The results are not sensitive to small changes in the prior specifications. Furthermore, the posterior results for the variance terms are quite different from the prior means.

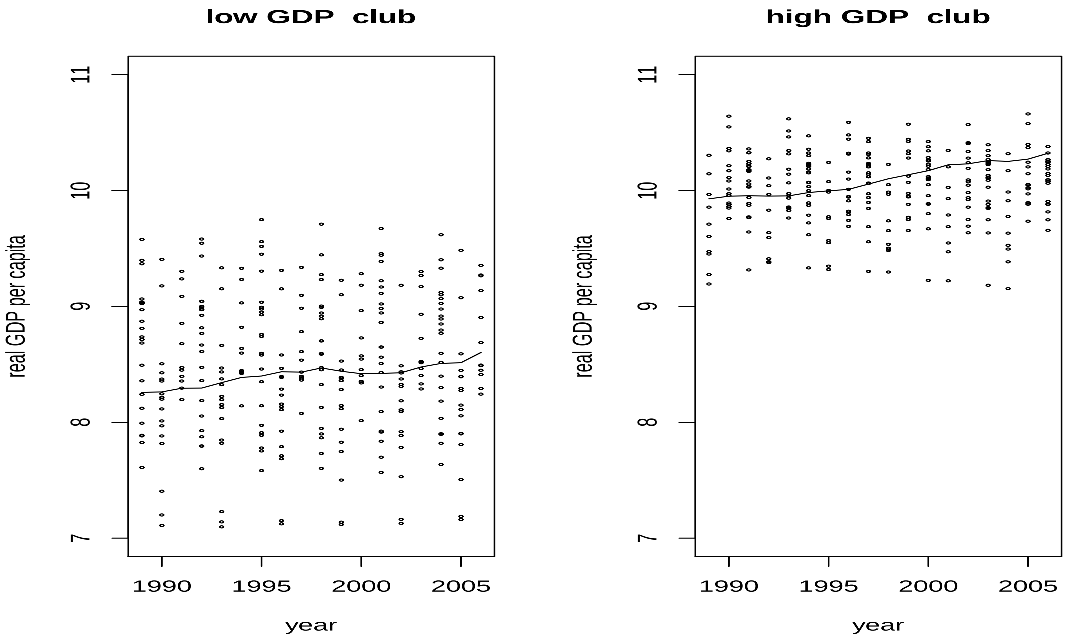
[8]We also applied the Markov switching model to this dataset. Club memberships in that case are quite similar to the results reported here.

Table 8: Ordered probit model extension (4): Club memberships with covariates (financial intermediary and stock market development indicators)

Countries that are always in the low GDP club:
Côte d'Ivoire, Egypt, India, Indonesia, Jamaica, Jordan, Morocco, Nigeria, Pakistan, Philippines, Sri Lanka, Thailand, Tunisia, Turkey.
Countries that are always in the high GDP club:
Australia, Canada, Denmark, Finland, Greece, Italy, Israel, Japan, Korea Rep., New Zealand, Portugal, Spain, United Kingdom, United States.
Countries that change clubs over time:
Argentina, Chile, Malaysia, Trinidad and Tobago, Venezuela RB.

Note: The table presents the posterior results for the ordered probit model, sample with 33 countries. We report countries that stay in the same club over the sample period together with the respective posterior clubs, and the countries that change clubs over time. Clubs *high GDP*, and *low GDP* are labeled according to posterior mean of GDP levels ($\mu_{j,t}$) in the last period. Club membership is determined by the posterior mode of the $S_{i,t}$ variable with an ordered probit specification.

Figure 4: Ordered probit model extension (4): Club memberships with covariates (financial intermediary and stock market development indicators)



Note: The figures show the mean posterior club levels (lines), and mean posterior club memberships (symbols) for the dataset with financial development indicators. Clubs *high GDP*, and *low GDP* are labeled according to posterior mean of GDP levels ($\mu_{j,t}$) in the last period. Club membership is determined by the posterior mode of the $S_{i,t}$ variable with an ordered probit specification.

Table 9: Ordered probit model extension (4): Initial GDP levels, growth rates and error variances for each club

	Club specification	
	low GDP	high GDP
GDP level $\mu_{j,t}$ in 1989	8.26	9.93
	(8.22, 8.30)	(9.93, 9.97)
Growth rate β_j	0.018	0.018
	(0.001, 0.031)	(0.000, 0.029)
Error variances $\sigma^2_{\nu,j}$	0.104	0.103
	(0.060, 0.172)	(0.058, 0.175)

Note: The table shows posterior means for initial GDP levels ($\mu_{j,1989}$), growth rates (β_j) and error variances ($\sigma^2_{\nu,j}$) for each club for each club, for the Ordered probit model extension. 2.25% and 97.5% percentiles of the posterior densities are reported in parentheses. Clubs *high GDP*, and *low GDP* are labeled according to posterior mean of GDP levels ($\mu_{j,t}$) in the last period.

ferent levels. Variations of GDP around the club-level (given by $\sigma^2_{\nu,j}$) are also similar across clubs. Hence the convergence clubs do not seem to be related to differences in GDP fluctuations.

Note that the results in terms of club levels and growth rates are in line with the results in Section 4.2: Most countries included in this smaller dataset were found to belong to the *medium* or *high* GDP clubs in the previous analysis. Table 9 shows that the club-specific GDP growth rates in the smaller dataset are around 2%, similar to the average GDP growth rate within the medium and high GDP clubs found before.

We now turn to the key aspect of this model, namely the effects of initial conditions and financial development indicators on GDP in the short-run and the long-run. Table 10 reports the posterior mean and mode values for the short- and long-run coefficients ψ^s and ψ^l, together with the posterior probability that the respective coefficient is positive.

We first discuss the long-run effects of the covariates reported in the top panel of Table 10. Recall that a positive coefficient indicates that the probability of belonging to the club with a higher average GDP level is increasing with the respective covariate. According to the posterior mean and mode values reported in Table 10, all factors we consider have such a positive effect on the GDP level in the long-run. Notice that initial condition is the only covariate that is constant over time. Hence the substantial effect of this covariate explains the reported persistence in club memberships.

The significance of these long-run effects is shown in Table 10 by the posterior probability that the respective coefficient is positive. These posterior probabilities exceed 0.9 for all variables, indicating that the long-run effects are quite significant.

Next, we consider the short-run effects of financial development indicators, re-

Table 10: Ordered probit model extension (4): Posterior results for the effects of financial development indicators

Long-run effects of financial development indicators			
	mean	median	post. prob.[a]
initial GDP	4.07	4.09	1.00
Financial intermediary development:			
Bank assets	0.47	0.47	0.94
Commercial/Central Bank	2.18	2.14	0.99
Stock market development:			
turnover	0.67	0.66	1.00

Short-run effects of financial development indicators			
	mean	median	post. prob.[a]
Financial intermediary development:			
Bank assets	-0.36	-0.36	0.16
Commercial/Central Bank	-1.27	-1.31	0.17
Stock market development:			
turnover	-0.09	-0.09	0.00

Note: The table summarizes the posterior results for the effects of financial development indicators: coefficients for the financial intermediary development variables and the stock market development variable.
[a] denotes the posterior probability that the coefficient is positive.

ported in the bottom panel of Table 10. A positive coefficient in this case means that the fluctuations of countries' GDP around the long-run path is affected positively by the respective factor. According to posterior mean and mode values, all factors we analyze have a negative effect on GDP in the short-run. This result is opposite to the long-run effects, and supports the evidence documented by Loayza and Ranciere (2006).

The significance of the short-run effects differs across variables. The posterior probability of a positive coefficient for stock market development in Table 10 is zero, indicating that this variable has a clear negative effect in the short-run. On the other hand, the posterior probabilities of positive short-run effects for the financial development indicators are around 15%, corresponding to posterior probabilities around 85% for negative short-run effects. Hence the negative effects of financial development indicators in the short-run are less clear. Therefore we conclude that financial development has a deteriorating effect on the countries' GDP levels mainly through changes in stock market development.

5 Conclusion

In this paper we develop a statistical approach to model the GDP convergence process for a large set of countries, and to assess the short-run and long-run effects of financial development on the GDP process. We introduce a novel Markov Chain State Space Model that allows for changes in club memberships over time. We further extend this model allowing for certain covariates to affect the club memberships, as well as the short-run fluctuations around the long-run GDP levels.

In an empirical application to a large cross-section of countries we find that the club memberships are quite persistent over time, but nevertheless the composition of the clubs changes substantially during the time period 1970-2007. This result points out the importance of taking the dynamic properties of the GDP data into account. In terms of the factors affecting club memberships, we first note that initial conditions, measured by initial real GDP per capita, are important determinants of club membership (for a subset of these countries). Furthermore, we find that an increase in the level of financial development can move a country to a higher GDP club. In terms of the short-run effects of financial development, we find a deteriorating effect of financial development specifically through stock market development.

As a final point, we note that the model we propose does not explicitly deal with changing number of clubs over time. In future work, we intend to extend our model allowing for changing number of clubs over time.

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