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.

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1 Introduction

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

It is well documented that the pure cross-sectional analysis of convergence has severe pitfalls. These criticisms can be summarized by two main points. First, analyzing average GDP levels or growth rates brings potential misspecification problems since this kind of data cannot uncover the time series dynamics of the GDP process (see e.g. Quah (1993), 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 the GDP growth rates, as the former is an exact definition of the catch-up process (see Quah (1993), Friedman (1992), Evans (1998) and Bianchi and Menegatti (2007) among others).

Following these criticisms, several studies adopt the time series approach to convergence. In general, these studies focus on the GDP per capita gaps between the countries over time through cointegration relations and analyze whether the income disparities between countries are persistent (see e.g. Evans (1998), Pesaran (2007)). As opposed to the cross-sectional studies, time-series tests for convergence tend to not rejecting the no convergence null for 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 misleading. 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), 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. Still, the empirical studies in convergence clubs is far from consensus. 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 define a priori countries that follow similar GDP 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 explain the changes in the composition of the convergence clubs over time, but rather can 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 this 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) and Bloom *et al.* (2003), Canova (2004), Paap *et al.* (2005) 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 in our study is hence to model the convergence process for a large set of countries in terms of the GDP levels, accounting for changing intradistributional 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 different long-run paths in real GDP per capita levels. With respect to this question, we estimate models with different specifications, and identify the number of distinct groups within the data. Furthermore, instead of defining exogenous factors, such as regions, affecting the club memberships, we assess the club memberships endogenously, using the 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 allows countries to switch between GDP clubs/clusters over time. Hence the composition of the clubs are not fixed over time. We then analyze the countries that stay in the same club over the sample period, and those that change clubs over time.

Our third question concerns whether the composition of these GDP clubs can be explained by initial conditions and financial development[2]. The contradicting empirical results on the effect of financial development on growth are documented by several papers, such as 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 of this 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

[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.

model where there is a single long-run relationship between financial development indicators 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 priory group of countries that follow 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 Chain model 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 converge 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), and Paap *et al.* (2005) 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 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. 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 reminder 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 presents the results for application on the real GDP per capita series. Section 5 concludes.

2 Model Specification

The Markov Chain State Space Model we propose aims to identify the common paths (clusters) in the data. Note that in the economic growth context, we use the term 'convergence clubs' for the hidden groups of data. In the Markov Chain models literature, the term 'cluster' is more common in the literature. Therefore we adopt the latter terminology in model specification.

Let $J \in 1,\dots,N$ denote the number of clusters in the data. Given J, and the cluster memberships, real GDP per capita level $y_{i,t}$ of country $i \in 1,\dots,N$ at time $t \in 1,\dots,T$ is explained by a linear model:

$$y_{i,t} \quad = \quad \mu_{j,t} + x^s_{i,t}\psi^s + \varepsilon_{i,t} \tag{1}$$

where country i belongs to cluster $j \in 1,\dots,J$ at time t, and $\varepsilon_{i,t} \sim NID\,(0, \sigma_i^2)$. Note that $\mu_{j,t}$ is the GDP level of cluster j at time t, and the explanatory variables in $x^s_{i,t}$ aim to capture the fluctuations of the GDP series around the long-run path defined by $\mu_{j,t}$.

Latent cluster levels $\mu_{j,t}$ in (1) follow a random walk process with a constant drift[3]:

$$
\begin{aligned}
\mu_{j,t} &= \mu_{j,t-1} + \beta_{j,t} + \nu_{j,t} && (2)\\
\beta_{j,t} &= \beta_{j,t-1} && (3)
\end{aligned}
$$

where $\beta_{j,t}$ for $t \in 1, \ldots, T$ denotes the real GDP per capita trend for cluster j, and $\nu_{j,t} \sim NID\left(0, \sigma^2_{\nu,j}\right)$.

At $t = 0$, cluster levels and trends follow a normal distribution:

$$
\begin{bmatrix} \mu_{j,0} \\ \beta_{j,0} \end{bmatrix} \sim N\left(\begin{bmatrix} \bar{\mu}_j \\ \bar{\beta}_j \end{bmatrix} \begin{bmatrix} \Sigma_\mu & 0 \\ 0 & \Sigma_\beta \end{bmatrix}\right) \tag{4}
$$

The next step is to incorporate unknown cluster memberships in the Markov Chain model. Let $S_{i,t} \in 1, \ldots, J$ denote latent cluster for country i at time t. Equation (1) becomes:

$$
\begin{aligned}
y_{i,t} &= H_{i,t}\mu_t + x^s_{i,t}\psi^s + \varepsilon_{i,t} && (5)\\
H_{i,t} = H\left(S_{i,t}\right) &= \begin{bmatrix} I\left[S_{it} = 1\right] & \ldots & I\left[S_{it} = J\right] \end{bmatrix} && (6)
\end{aligned}
$$

where $\mu_t = \left[\mu_1, \ldots, \mu_J\right]'$ is the vector of cluster levels for each cluster at time t, and $I[.]$ is the indicator function which takes the value of 1 if the argument is true, and 0 otherwise.

Therefore when both cluster levels and cluster memberships are defined as latent variables, the Markov Chain model is nonlinear. Given the cluster memberships, the GDP series follows the long-run level and trend of the respective cluster. However, since the cluster memberships are not fixed over time, the long-run paths and the trend of the individual series are allowed to change through the country's respective cluster memberships.

The Markov Chain Model we propose extends the standard State Space formulation in the following way: since the cluster memberships S_t are not known beforehand, the transition matrix H_t for $t = 1, \ldots, T$ in the observation equation is an extra time-dependent, unobserved variable. Therefore the clusters S_t and the indicator matrix H_t are to be determined from the data as well. In this respect, equations (2, 3, 4, 5, 6) define a non-linear State Space Model with two sets of latent variables, namely the latent common levels and trends within subgroups of data, and a latent cluster membership for each observation.

We propose two different formulations for the cluster memberships. The first specification considers a 1st order Markov process for the state memberships, where GDP club formation endogenously, without defining certain factors affecting the club formation or memberships. The second step in our analysis is to see whether

[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.

selected covariates can explain club formations. For this reason we use an ordered probit model for the cluster memberships, conditional on the selected covariates.

Note that there are several possible ways model GDP clubs using latent variables, and the regressors affecting these club memberships. The choice of our models depends on the properties of the GDP data. First, more general models accounting for the latent structure in the GDP series, such as Markov Chain models with time varying parameters, require a rather large number of observations. Alhough we consider a large set of countries, the number of time periods in GDP data is quite restricted. Therefore the use of more general latent class models is not appropriate for this dataset.

In order to assess effects of regressors on GDP clubs, we choose ordered probit models for cluster memberships, since it provides a natural ranking in the GDP clubs. A positive effect of regressors in the ordered probit model implies that the probability of a country to belong to a higher GDP cluster increases with the covariates. Other methods, such as a 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). These two formulations for cluster memberships are explained in Sections 2.1 and 2.2.

2.1 Modeling cluster memberships as a 1st order Markov Chain process

Let p_{kj} denote the probability that an observation in cluster k belongs to cluster j in the next period, for $j, k \in \{1, \ldots, J\}$. The following matrix defines the transition probabilities between clusters:

$$P = \begin{bmatrix} p_{11} & & p_{1J} \\ & \ddots & \\ p_{J1} & & p_{JJ} \end{bmatrix} \tag{7}$$

where $p_{kj} = Pr\left(S_{i,t} = j \mid S_{i,t-1} = k\right)$ for all i, t. By definition, the Markov Chain probabilities are such that $p_{kj} \in [0, 1]$ for all k, j and $\sum_k p_{kj} = 1$ (see Hamilton (1994) p. 692). Note that this formulation imposes state dependencies in the cluster memberships over time, but not across cross-sections.

2.2 Ordered Probit Model for cluster memberships

In this formulation, the latent cluster memberships are determined by selected covariates according to the following equations:

$$S_{i,t} = j \text{ iff } \left(\gamma_{j-1} < s^*_{i,t} \leq \gamma_j\right) \tag{8}$$

$$s^*_{i,t} = x^l_{i,t}\psi^l + \zeta_{i,t} \tag{9}$$

where γ_j for $j = 0, \ldots, J$ are the thresholds for the ordered probit model with $\gamma_0 = -\infty$ and $\gamma_J = \infty$, and $\zeta_{i,t} \sim \text{NID}\,(0, 1)$, where the variance of $\zeta_{i,t}$ is fixed at 1 for identification. $x^l_{i,t}$ are the variables affecting the cluster membership, hence the long-run level and the growth rate for each observation. In the empirical analysis, $x^l_{i,t}$ corresponds to the initial conditions and financial development indicators.

3 Estimation and Inference

Since we have a nonlinear State Space Model with two sets of latent variables, we use Bayesian Estimation and Gibbs Sampling for the estimation (Geman and Geman, 1984). The use of Bayesian Estimation methods are common in particular for the Markov Chain models, see e.g. Carter and Kohn (1994). Frühwirth-Schnatter and Kaufmann (2008) also provides the Gibbs Sampling schemes for Markov Chain models with cluster probabilities depending on certain covariates. The Gibbs Sampling steps we summarize below are similar to Frühwirth-Schnatter and Kaufmann (2008) except for updating the latent state variables (i.e. cluster means and trends) and cluster probabilities for the ordered probit model extension.

Gibbs Sampling Scheme:

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

- Draw σ^2_ν from $p\left(\sigma^2_\nu \mid \{y_t\}_{t=1}^T, \alpha\sigma^2, \psi^s, \{S_{i,t}\}_{t=1,n=1}^{T,N}\right)$, with inverse Gamma (conjugate) priors
- Draw $\{\sigma^2_i\}_{i=1}^N$ from $p\left(\sigma^2 \mid \{y_t\}_{t=1}^T, \alpha\sigma^2_\nu, \psi^s, \{S_{i,t}\}_{t=1,n=1}^{T,N}\right)$, with inverse Gamma (conjugate) priors
- Draw ψ^s from $p\left(\psi^s \mid \{y_t\}_{t=1}^T, \alpha, \sigma^2, \sigma^2_\nu, \{S_{i,t}\}_{t=1,n=1}^{T,N}\right)$, with flat priors

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

- $\{\alpha_t\}_{t=1}^T$ from $p\left(\mu, \beta \mid \{y_t\}_{t=1}^T, \sigma^2, \sigma^2_\nu, \psi^s, \{S_{i,t}\}_{t=1,n=1}^{T,N}\right)$, via Kalman Filter

(c) Given the model parameters and the latent state variables, draw cluster memberships:

- Draw S_{it} for $i = 1, \ldots, N$, $t = 1, \ldots, T$ from $p\left(S \mid \{y_t\}_{t=1}^T, \alpha\sigma^2, \sigma^2_\nu, \psi^s\right)$

Note that step (c) in the Gibbs Sampling scheme depends on whether we use the 1st order Markov Chain model or the ordered probit model for the cluster memberships. For the 1st order Markov Chain model, Dirichlet priors can be used as conjugate priors (Carter and Kohn, 1994). For the ordered probit model on the other hand, we need to draw the probit coefficients together with the latent variable $s^\star$ and the probit thresholds $\bar{\gamma}$ in (8) and (9):

- Draw threshold variables: $\gamma_j \sim U(\bar{\gamma}_{j-1}, \bar{\gamma}_{j+1})$ under flat priors (Carter and Kohn, 1994):

$$\begin{aligned} \bar{\gamma}_{j-1} &= \max\{max\{s^*_{i,t} \mid S_{i,t} = j-1\}, \gamma_{j-1}\} \quad (10) \\ \bar{\gamma}_{j+1} &= min\{min\{s^*_{i,t} \mid S_{i,t} = j+1\}, \gamma_{j+1}\} \quad (11) \end{aligned}$$

- Draw the ordered probit model parameters ψ^l under flat priors

Posterior Classification: For the posterior classification of observations, the posterior classification probability can be calculated as follows (Frühwirth-Schnatter and Kaufmann, 2008):

$$Pr\left[S_{i,t} = j \mid \{y_t\}_{t=1}^T\right] \approx \frac{1}{M} I\left[S_{i,t}^{(m)} = j\right] \quad (12)$$

where M is the total number of MCMC draws, and $j \in 1, \ldots, J$

Choosing the number clusters: An important feature of the Markov Chain Models is the choice of the number of clusters, J. Generally, both the studies adopting the frequentist or Bayesian approach rely on the information criteria for the choice of the number of clusters in the data[4]. Following these studies, we compare the information criteria for the different models.

In the Bayesian analysis, 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) shows this result in particular for the hierarchical models, and propose *deviance information criteria* (DIC). For the 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 where 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) proposes 8 different DIC specifications. We use the conditional DIC (*DIC7*) they propose since this specification implicitly accounts for the latent variables as additional parameters. BIC and DIC criteria are defined as:

$$\begin{aligned} BIC_J &= -2\tilde{l}_J(\theta) + ln(N \times T) \times p_J \quad (13) \\ DIC_J &= -4\hat{l}_J(\theta) + 2l_J\left(\hat{\theta}\right) \quad (14) \end{aligned}$$

where θ are the posterior draws of the model parameters, p_J is the number of parameters for the model with J clusters, and $l_J(\theta)$ is the log-likelihood function evaluated at model parameters θ and number of clusters J. $\hat{x}$ and $\tilde{x}$ denote the mean and the maximum value of variable x, respectively.

[4] An extension of this could be to employ Dirichlet Process (DP) Priors on the number of clusters. We do not employ this extension here, since the model would be more complicated, and the model with DP priors would require much more computational power.

4 Empirical Results

We apply the 1st order Markov Chain model and the extension with club (cluster) probabilities depending on covariates on the log real GDP per capita series. The models are estimated using Ox (Doornik, 2006) programming language. For the extended model with an ordered probit model for the club memberships, we consider the initial conditions and financial development as possible factors affecting the club memberships. Section 4.1 presents the data for the application. The results for the 1st order Markov Chain model and the ordered probit model extension are presented in Section 4.2 and Section 4.3, respectively.

4.1 Data

The data for real GDP per capita is taken from Penn World Tables (PWT), version 6.3, Heston *et al.* (2009). We take the natural logarithms of the data. For the Markov Chain Model for GDP levels, we consider a balanced panel data for 163 countries, for the period between 1970–2007. The included countries and the data plots are given in Table 1.

–Insert Table 1 about here–

For the banking development and financial intermediary development we consider three conventional measures in the literature, namely Deposit Money Bank Assets as a percentage of GDP (*Bank assets*) and Commercial bank assets as a percentage of total assets (*Commercial/Central bank*) and stock market turnover ratio (*turnover*). For extensive reviews on the financial development indicators, see Beck and Levine (2004), Aghion *et al.* (2005), Loayza and Ranciere (2006), Méon and Weill (2008), Rioja and Valev (2004)). Two of these measures, namely Deposit Money Bank Assets and Commercial bank assets are measures of financial intermediary development. Turnover ratio on the other hand indicates stock market development (Beck and Levine, 2004). For financial development indicators, we use the data from Beck *et al.* (2000) database on financial development indicators, revised on May 2009.

The empirical difficulty in grouping the countries depending on the financial development is the difference between the short-run and long-run effects of financial development: The empirical studies confirm that the effect of financial development on GDP can be different in the short-run and long-run. We define the long-run variables as averages of the financial development indicators over 5-year windows. Furthermore, in order to control for the effect of initial conditions on club memberships, we include the real GDP per capita levels of countries as an extra variable affecting the club membership in the long-run. For the short-run variables on the other hand, we use the lagged financial development indicators, in differences from the long-run levels, calculated as averages over 5 consecutive years. This controls for the multicollinearity between the short-run and long-run factors.

Including the financial development indicators to the data decreases the time-series and the cross-sectional dimension of the data to 33 countries over the period 1989-2006. The choice of the time period and the countries are made according to data availability. The included countries for this model are reported in Table 2. Note that the sample size significantly decreases when we include the financial development indicators, especially stock market development indicators in the model. There are several options, such as Expectation Maximization algorithm, that could be used to account for the missing data. We do not adopt these approaches since the financial development data has missing values in blocks rather than at random time points. Using these methods to assess the missing data in this case can therefore cause misleading results. It is also important to note that the both the cross-sectional and the time-series dimensions of the data are of concern for the model we propose. Intuitively, extracting the time-dependent latent variables in the model relies on the time series dimension of the data. On the other hand, the cross-section dimension of the data is required for a comparative analysis of the convergence clubs. We choose the number of countries and the time period to maximize the total number of observations in the dataset.

4.2 MC model results

We first apply the model proposed in Section 2 on the log real GDP per capita for 163 countries for the period 1970-2007. In terms of the convergence clubs, the common practice is to employ two to four clubs in terms of GDP clubs (see e.g. Hansen (2000), Canova (2004), Paap *et al.* (2005)). This specification also brings an advantage in interpretation: The clubs can be ranked according to the degree of mean GDP levels. We consider models with two to seven clubs, together with a single club model. Note that the single club model indicates a pooled regression. We then rely on the information criteria comparisons to choose between these different specifications.

The BIC and DIC comparisons for the different models are given in Figure 1, together with posterior log-likelihood summaries. We report the mean posterior conditional log-likelihood, maximum value of the conditional posterior log-likelihood and the conditional log-likelihood at mean posterior parameters. Log-likelihood in the mean posterior parameters is calculated as the value of the log-likelihood given the mean values of the model parameters, together with mean posterior club levels and memberships.

According to the information criteria comparisons, both information criteria decrease with the number of clubs in the model. We do however see that DIC has a higher penalty for the number of clubs, since the difference between the BIC and DIC lines in Figure 1 increase with the number of clubs in the model. A visual inspection however shows that the highest decrease in the information criteria is achieved when we move from two to three clubs. The same result holds when we consider the posterior log-likelihoods. The highest increase in posterior log-likelihoods are achieved for the model with three convergence clubs. We therefore choose the model with three clubs as our base model.

–Insert Figure 1 about here–

Persistence in club memberships: Table 3 presents the mean posterior transition probabilities for the model with three convergence clubs. The clubs *high GDP*, *medium GDP*, and *low GDP* are defined according to the average posterior club levels in the sample period. The club levels are the elements of the vector μ_t in equation (5).

The diagonal elements of the mean posterior transition matrix are quite close to 1. This result indicates a high persistence in the club memberships. This is an expected result since the shifts in annual GDP paths should be rather smooth: The changes in possible factors affecting the GDP levels, such as financial development indicators, increase gradually over time. Furthermore, there are no sudden shifts between the low GDP and high GDP clubs. The probability of a country in the low GDP club to switch to the high GDP club is almost zero, and vice versa.

Note that the persistence in the transition probability matrix does not necessarily imply a persistence in the club formations over time, but rather gradual changes in the club compositions. The transition probability matrix simply reports the average transition probabilities. For instance, when a country stays in the low GDP club at the beginning of the sample period, and the medium GDP club during the rest of the sample period, there is only a single change in the club membership over the sample. However, this kind of a change does indicate a structural change for this country, and is an important aspect of our analysis on terms of the composition of GDP clubs. This evidence is more clear in Figure 2. Figure 2 shows the number of countries in each club over the sample period. The composition of clubs do seem to change through time. In particular, the number of countries in the lowest GDP club seem to decrease. This argument is in line with the bimodality argument (Quah, 1996), however we find that the decrease in the number of countries in the *low GDP* club causes this result instead of a disappearing middle income class.

–Insert Figure 2 about here–

Figure 3 presents the posterior results for the club levels and memberships for the three club model. The solid lines represent the club levels calculated as the mean posterior values for μ in equation (5). It can be seen that the club levels are quite different across groups.

–Insert Figure 3 about here–

Composition of convergence clubs: Table 4 reports the countries that stay in the same club over the sample period. Table 5 on the other hand reports the countries that change clubs at least for once during the sample period. It can be seen that around one third of the countries change clubs at least once during the sample period. This evidence can only be extracted when we allow for changes in the composition of GDP clubs.

–Insert Table 4 and Table 5 about here–

According to Table 4 and Table 5 most sub-Saharan African countries in the sample are in the low GDP club throughout the sample period. Latin American countries are in general in the medium GDP club. Oil producing countries, except for Oman, are in the high GDP club throughout the sample period. Oman is found to belong to the high GDP club except for the year 1973.

Table 6 presents selected countries that change clubs over the sample period, and the selected years of these changes. In particular, the MC model captures several Asian countries *(*Asian tigers) switching to a higher GDP club compared to their club in 1970s. Furthermore, some EU member countries, such as Cyprus, Hungary and Malta switch to the high GDP club.

–Insert Table 6 about here–

For the MC model, 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 depict that it is important to analyze the GDP clubs in a flexible setting which allows for changes in club memberships over time.

Differences in growth structures across clubs: Table 7 presents the average posterior growth rates for each cluster. We can see that the common growth rates for *high GDP* and *medium GDP* clusters are both around 2%. *Low GDP* cluster on the other hand has much lower growth rates. Therefore there is no indication of convergence between separate groups: Although the number of countries within each group change through time, we cannot find convergence across the distinct clusters. The clusters rather define three different long-run levels where the higher GDP clusters (*high GDP* and *medium GDP*) exhibit a larger trend than the *low GDP* cluster.

–Insert Table 7 about here–

4.3 Estimation results for the MC model with financial development indicators

The purpose of this section is to analyze possible explanatory factors affecting the GDP clubs in the short-run as well as in the long-run. We apply the Markov Chain model with the transition probabilities depending on certain covariates. Similar to the previous analysis, the dependent variable is the annual log real GDP per capita levels. In particular, club memberships, hence the long-run GDP levels of countries are explained by initial real GDP per capita levels and the long-run averages of the financial development indicators explained in Section 4.1. We also check whether financial development indicators can explain the short-run fluctuations in GDP. We include financial development indicators explained in Section 4.1 as covariates explaining the fluctuations of GDP per capita levels around the club levels. To prevent possible endogeneity between the annual financial development indicators and the

GDP levels, we include the first lags of financial development indicators as short-run factors in the model.

Note that this selection of covariates lead to a much smaller dataset compared to the one we analyze in Section 4.2. Therefore the number of convergence clubs can be different than the one for 163 countries included in Section 4.2. Hence we first analyze the convergence clubs in this dataset without covariates. Afterwards we use the ordered probit model to check the effects of financial development indicators as well as initial GDP levels on long-run GDP levels as well as the short-run fluctuations in GDP. This approach allows us to first check the GDP clubs endogenously, and then to assess whether the formation of these clubs can be explained by the selected covariates.

Analysis of convergence clubs without covariates: We first employ the model in Section 2.1 on the GDP data of 33 countries for the period 1989-2006, for which financial development data is available. Figure 4 shows the information criteria comparisons and posterior log-likelihood summaries for the Markov Chain models with different number of GDP clubs. We report the mean posterior conditional log-likelihood, maximum value of the conditional posterior log-likelihood and the conditional log-likelihood at mean posterior parameters.

–Insert Figure 4 about here–

Figure 4 shows that DIC values decrease with the number of clubs, while BIC has its minimum for the three-club model. Furthermore, the biggest jumps in both information criteria are achieved when we move from the single-club model to the two-club model. Hence for the smaller dataset, we conclude that the two-cluster model and the three-cluster models can be appropriate. This result is in line with Section 4.2: most of the countries in the small sample fall in the *medium* and *high* GDP clubs according to the Markov Chain model results presented in Section 4.2. Therefore we consider two and three clubs for the Markov Chain model and the ordered probit model for this dataset.

Table 8 shows the posterior cluster memberships for the 1st order Markov Chain model with two and three clubs. Table 8 shows that cluster membersips are quite persistent compared to the dataset with 163 countries, but some countries do change clubs over time. Average long-run GDP levels and club memberships for both models are shown in Figure 5. For the three-club model, a visual inspection shows that the difference between the medium and high GDP cluster levels is less apparent at the end of the sample period, indicating convergence of these clusters in terms of long-term levels.

–Insert Table 8 about here–

–Insert Figure 5 about here–

The effects of financial development indicators: Next we implement the ordered probit model in Section 2.2 for GDP data, using financial development indicators as long-run and short-run factors affecting GDP clubs and short-run deviations from the club levels, respectively. We focus on the models with two and three clubs since the model without covariates we analyzed before indicates these specifications for the data we consider.

Table 9 summarizes the posterior club compositions for the two and three cluster models. Similar to the Markov Chain model results for this dataset, the cluster membership is more persistent. In both models, 15% of the countries are found to change clusters, according to the posterior cluster memberships[5]. Furthermore, posterior club memberships, calculated as the mean posterior clusters, are similar to those for the Markov Chain model reported in Table 8.

–Insert Table 9 about here–

Figure 6 shows the average club levels and the memberships for both models. Similar to the Markov Chain model results for this dataset, the difference between the long-run levels of the medium and high GDP clusters is less clear at the end of the sample period, indicating convergence of these clusters in terms of long-term levels. The average common trends shown in Table 10 also confirm this hypothesis. For the model with three GDP clubs, the medium GDP club is found to have a considerably higher trend than the high GDP club. For this reason, we focus on the two club results in terms of the effects of financial development indicators.

–Insert Figure 6 about here–

–Insert Table 10 about here–

Long-run effects of financial development on GDP clusters: Table 11 summarizes the posterior results for the short-run effects of financial development together with the long-run determinants of club memberships. In terms of the long-run effects of financial development, a positive coefficient for these variables indicates that the probability of belonging to the club with a higher average GDP level is increasing with financial development. Table 11 shows that initial real GDP per capita, financial intermediary development indicators, as well as the stock market development indicators are important factors affecting the club memberships.

–Insert Table 11 about here–

According to the mean and median posterior summaries, initial GDP is by far the most important factor affecting the club membership. This result supports the studies which exogenously cluster the countries according to the initial GDP levels (see Durlauf and Johnson (1995) and Hansen (2000)). We do however find that financial development indicators affect the club memberships significantly. For all financial development indicators in the model, the posterior probability that the coefficient is positive is above 90%.

[5] Similar to the MC model results, the reported cluster membership is the cluster for which the observation has maximum mean posterior probability.

Short-run effects of financial development: Short-run effects of financial development indicators, shown in Table 11, are less clear. Considering the mean and median of the posterior results for financial intermediary development, we do find a negative effect of financial intermediation on GDP levels in the short-run. However, the posterior probabilities of a negative effect for financial intermediary development are around 85%. Therefore we cannot conclude that these effects are not zero.

For the stock market development effects, we do find a clear negative short-run effect on GDP. The posterior probability of this negative effect is almost 1%. Therefore we conclude that financial development has a deteriorating effect on the countries' GDP levels mainly through the 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 can capture the changes in club memberships over time. We further extend this model allowing for certain covariates to affect the club memberships, as well as the fluctuations around the long-run GDP levels. We find that the club memberships are quite persistent over time, but the composition of the clubs change significantly over time. 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 find that initial conditions, measured by initial real GDP per capita, are by far the most important factors affecting convergence clubs. However, we do find that an increase in the level of financial development can move a country to a higher GDP cluster. 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 clusters over time. In future work, we intend to extend our model allowing for changing number of clusters over time.

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Tables and Figures

Table 1: Included countries in the MC model

Included countries - 1st order MC model
Afghanistan, Albania, Algeria, Angola, Antigua and Barbuda, Argentina, Australia, Austria, Bahamas, The, 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 table presents 163 included countries for the MC model.

Table 2: Included countries in the ordered probit model

Included countries - Ordered probit model
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 table presents 33 included countries for the MC model.

Table 3: Mean posterior 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 transition probabilities (matrix P in equation 7) for the Markov Chain model, for the dataset with 163 countries, period between 1970–2007.

Table 4: 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, The 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 club over the sample period together with the respective posterior clubs, for the Markov Chain model, dataset with 163 countries, period between 1970–2007. For each observation, reported posterior club is the club for which the observation has the maximum mean posterior club probability.

Table 5: 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, for the Markov Chain model, dataset with 163 countries, period between 1970–2007. For each observation, reported posterior club is the club for which the observation has the maximum mean posterior club probability.

Table 6: 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 Chain model, dataset with 163 countries for the period between 1970–2007. The year of change is indicated in parentheses.
[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.

Table 7: Posterior trends for the clubs

	low GDP	medium GDP	high GDP
mean growth	0.006	0.021	0.023
median growth	0.005	0.017	0.021
95% HPD region	(0.002,0.12)	(0.012,0.040)	(0.020,0.036)

Note: The table presents the posterior means, medians and 95% HDP regions for the club trends (common trends for the observations within the same club), for the Markov Chain model, dataset with 163 countries for the period between 1970–2007.

Table 8: Posterior cluster memberships

Results for the model with two clubs

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:
Argentina, Australia, Canada, Denmark, Finland, Greece, Israel, Italy, Japan, Korea Rep., New Zealand, Portugal, Trinidad and Tobago, United Kingdom, United States.

Countries that change clubs over time:
Chile, Malaysia, Venezuela RB.

Results for the model with three clubs

Countries that are always in the low GDP club:
Côte d'Ivoire, Egypt, India, Indonesia, Morocco, Nigeria, Pakistan, Philippines, Sri Lanka, Turkey.

Countries that are always in the medium GDP club:
Argentina, Chile, Malaysia, Venezuela RB.

Countries that are always in the high GDP club:
Australia, Canada, Denmark, Finland, Greece, Italy, Japan, New Zealand, Spain, United Kingdom, United States.

Countries that change clubs over time:
Jordan, Korea Rep., Trinidad and Tobago, Tunisia, Israel, Portugal, Thailand, Jamaica.

Note: The table presents the posterior cluster memberships for the two-club and three-club Markov Chain models for the smaller sample with 33 countries, without explanatory variables for GDP levels. For each observation, reported posterior club is the club for which the observation has the maximum mean posterior club probability.

Table 9: Posterior club memberships for the ordered probit models

Results for the model with two clubs

Countries that are always in the low GDP club:
Côte d'Ivoire, Egypt, Indonesia, India, Jamaica, Jordan, Sri Lanka, Morocco, Nigeria, Pakistan, Philippines, Thailand, Tunisia, Turkey.

Countries that are always in the high GDP club:
Australia, Canada, Denmark, Spain, Finland, United Kingdom, Greece, Israel, Italy, Japan, Korea Rep., New Zealand, Portugal, United States.

Countries that change clubs over time:
Argentina, Chile, Malaysia, Trinidad and Tobago, Venezuela RB.

Results for the model with three clubs

Countries that are always in the low GDP club:
Côte d'Ivoire, Egypt, Indonesia, India, Sri Lanka, Morocco, Nigeria, Pakistan, Philippines, Turkey.

Countries that are always in the medium GDP club:
Argentina, Chile, Jamaica, Korea Rep., Malaysia, Portugal, Trinidad and Tobago, Tunisia, Venezuela RB.

Countries that are always in the high GDP club:
Australia, Canada, Denmark, Spain, Finland, United Kingdom, Italy, Japan, United States.

Countries that change clubs over time:
Greece, Israel, Jordan, New Zealand, Thailand.

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. For each observation, reported posterior club is the club for which the observation has the maximum mean posterior club probability.

Table 10: Posterior club growth rates

Results for the model with two clubs		
	Low GDP	High GDP
mean growth	0.018	0.018
median growth	0.018	0.020
95% HPD region	(0.001, 0.031)	(0.000,0.029)

Results for the model with three clubs			
	Low GDP	Medium GDP	High GDP
mean growth	0.032	0.056	0.006
median growth	0.027	0.048	0.013
95% HPD region	(0.016, 0.080)	(0.036, 0.119)	(-0.032,0.019)

Note: The table presents the posterior results for the smaller sample with 33 countries. We report posterior means, medians and 95% HDP regions for the GDP trends for each club for the two-club model and the three club model.

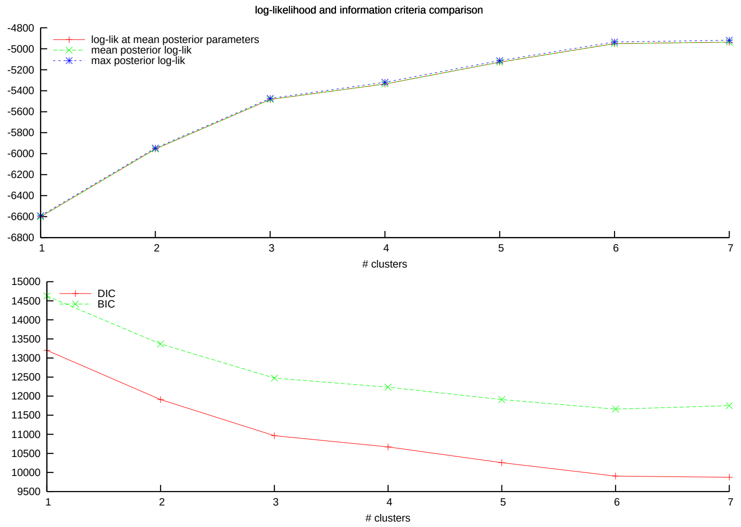
Table 11: Posterior results for the effects of financial development indicators

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

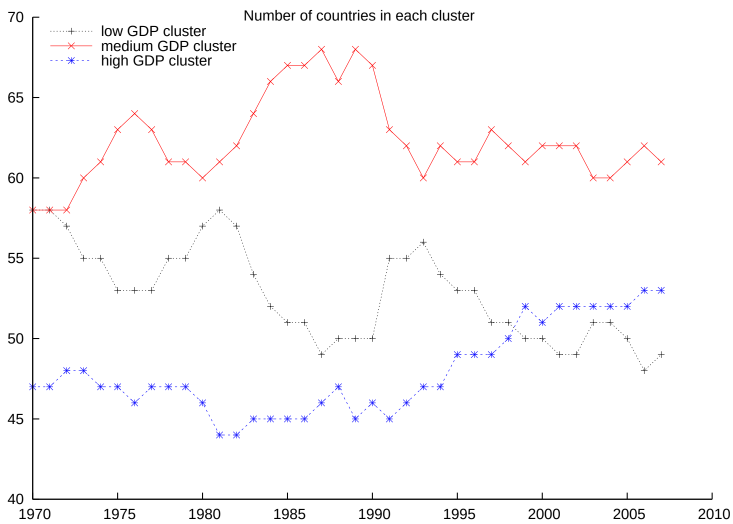
Note: The table summarizes the posterior results for the effects of financial development indicators, namely the coefficients for the financial intermediary development variables and the stock market development variable.
[a] denotes the posterior probability that the coefficient is positive.

Figure 1: Posterior log-likelihood summary and Information Criteria Comparisons



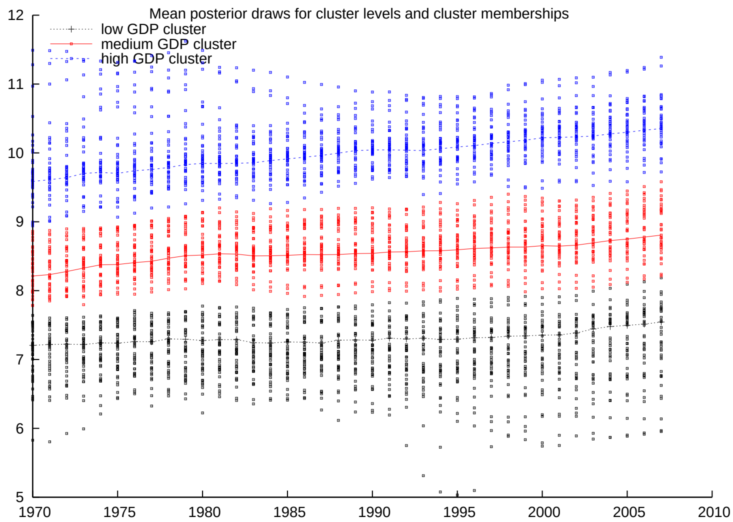
Note: The figure shows the posterior results for the 1st order Markov Chain models with 1 to 7 clubs, for the dataset with 163 countries. The top figure shows the posterior conditional log likelihood summaries: log-likelihood values at mean posterior parameters, mean posterior log-likelihood values,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

Figure 2: Number of countries in each club over time



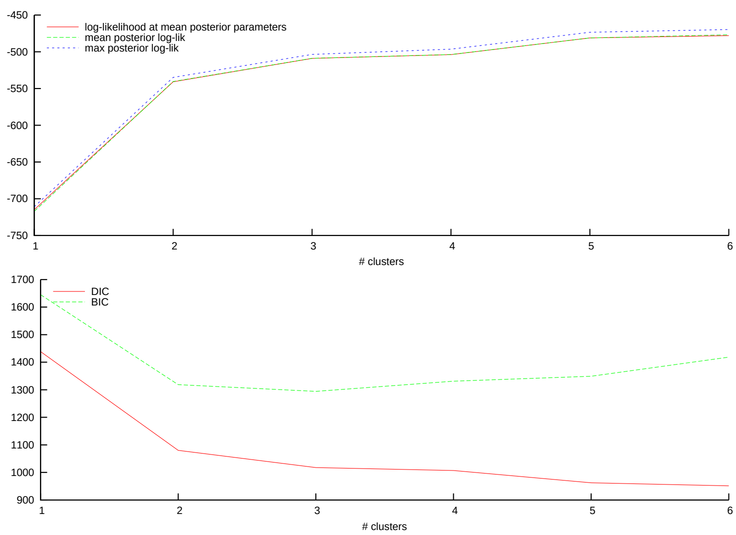
Note: The figure shows the number of countries in each club over the sample period for the three club model, for the dataset with 163 countries. For each observation, reported posterior club is the club for which the observation has the maximum mean posterior club probability.

Figure 3: Posterior Club Memberships: MC model



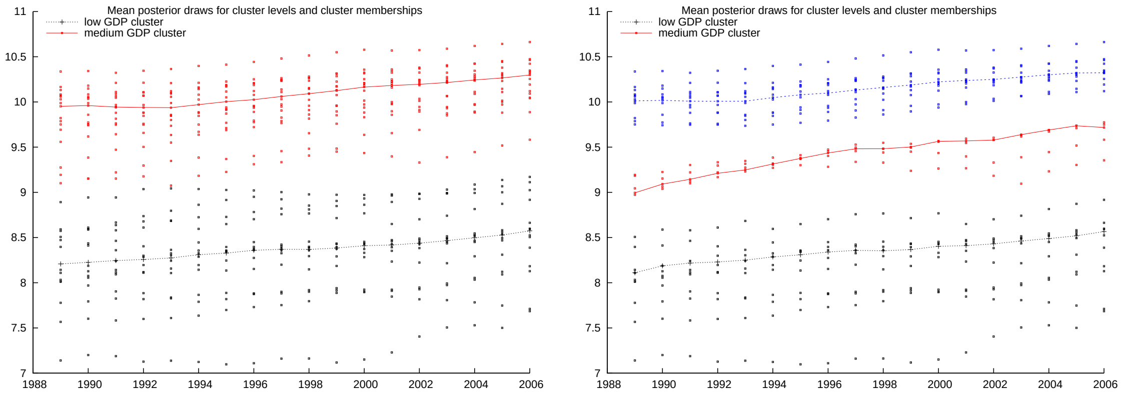
Note: The figure shows the mean posterior club levels (solid lines), and mean posterior club memberships (symbols), for the dataset with 163 countries. The club members are indicated by the same color as the respective club. For each observation, reported posterior club is the club for which the observation has the maximum mean posterior club probability.

Figure 4: Posterior log-likelihood summary and information criteria comparisons



Note: The figure summarizes the posterior results for the dataset with 33 countries, estimated by 1st order Markov Chain models with 1 to 6 clubs. The top figure shows posterior conditional log likelihood summaries: log-likelihood at mean posterior parameters, mean posterior log-likelihood, and maximum posterior log-likelihood. BIC and DIC for models with 1 to 6 clubs are shown in the bottom figure.

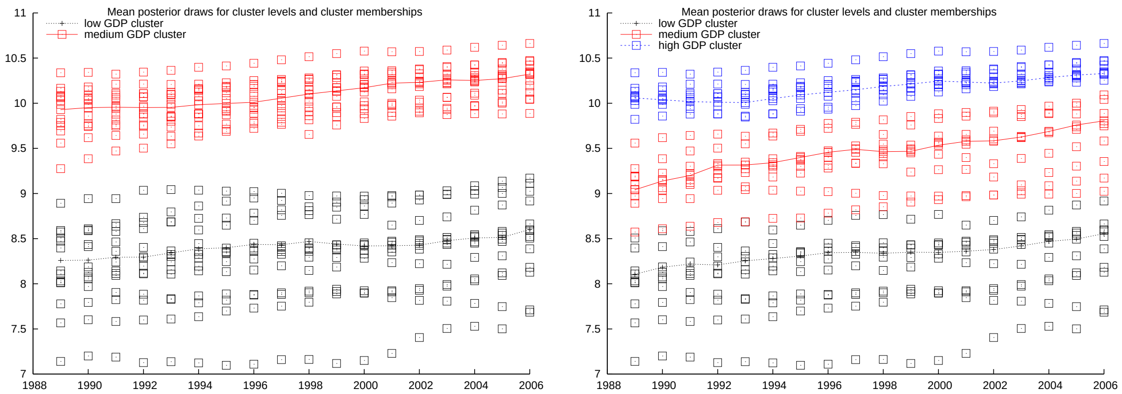
Figure 5: Posterior Club Memberships: Markov Chain models for the small sample



(a) Memberships for the two club model (b) Memberships for the three club model

Note: The figures shows the mean posterior club levels (solid lines), and mean posterior club memberships (symbols) for the 1st order Markov Chain model, dataset with 33 countries. The club members are indicated by the same color as the respective club. For each observation, reported posterior club is the club for which the observation has the maximum mean posterior club probability.

Figure 6: Posterior Club Memberships: Ordered Probit models



(a) Memberships for the two club model (b) Memberships for the three club model

Note: The figures shows the mean posterior club levels (solid lines), and mean posterior club memberships (symbols) for the ordered probit model, dataset with 33 countries. The club members are indicated by the same color as the respective club. For each observation, reported posterior club is the club for which the observation has the maximum mean posterior club probability.