CLUSTERING REGIONAL BUSINESS CYCLES

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Abstract

The aim of this paper is to show the usefulness of Finite Mixture Markov Models (FMMMs) for regional analysis. FMMMs combine clustering techniques and Markov Switching models, providing a powerful methodological framework to jointly obtain business cycle datings and clusters of regions that share similar business cycle characteristics. An illustration with European regional data shows the sound performance of the proposed method.

Keywords: business cycles, clusters, regions, finite mixture Markov models.

JEL classification: C22, C32, E32, R11.

Resumen

El objetivo de este trabajo es mostrar la utilidad de los modelos de Markov con mixturas finitas de distribuciones para el análisis regional. Estos modelos combinan técnicas de agrupamiento y modelos de Markov *Switching,* proporcionando un marco metodológico sólido que permite obtener de forma conjunta datados de los ciclos económicos regionales e identificar grupos de regiones que comparten características similares del ciclo económico. Se ilustra el buen funcionamiento del método propuesto con datos del PIB de las regiones europeas.

Palabras clave: ciclo económico, *clusters,* regiones, modelos de Markov con mixturas finitas de distribuciones.

Códigos JEL: C22, C32, E32, R11.

1 Introduction

Studying the regional dimension of business cycles is important to uncover the heterogeneity hidden in country analyses.[1] By dealing with a larger information set, new insights can be obtained, useful, for instance, when implementing economic policies. Nevertheless, the literature analyzing regional business cycles is relatively scant. This could be due to data limitations and technical difficulties to properly capture business cycles in small economic units.

The goal of this letter is to show the usefulness of Finite Mixture Markov models (FMMM), developed by Frühwirth-Schnatter and Kaufmann (2008), to identify common cyclical patterns among regions, that is, to show that the combination of clustering techniques and Markov Switching models provides a powerful methodological framework to analyze business cycles at a regional level and overcome the above-mentioned limitations. By using these techniques, it is possible to both obtain a business cycle dating and to identify clusters according to business cycle features. We present an empirical application for European regions.

2 Finite Mixture Markov Models for regional analysis

Business cycle analysis is usually carried out at national level and using quarterly or monthly data. The most common methods to obtain business cycle datings are the Bry and Boschan (1971) algorithm and Markov Switching models put forward by Hamilton (1989). From these individual datings, it is usual to analyze business cycle features, to detect patterns of synchronization or to build clusters of countries.[2] Analyzing the regional dimension introduces new challenges, especially for

[1] See, *e.g.*, Ramajo *et al.* (2008) for the European regions and Park and Hewings (2012) for the US states.

[2] Some examples are Gadea *et al.* (2017b), Harding and Pagan (2006) and Camacho *et al.* (2006).

dating business cycles of individual series. Note that the individual estimation of business cycles by regions usually exhibits large estimation errors because of short samples and high variability.[3] Paraphrasing Stock and Watson (2010), the "aggregate (at national level) and then date" approach is usually preferred, in spite of the subsequent loss of valuable information, to the "date and then aggregate" approach.[4]

Against this background, the model-based clustering approach for multiple time series developed by Frühwirth-Schnatter and Kaufmann (2008) is suitable to analyze regional business cycles.[5] This method can be used for finite mixtures of Markov Switching autoregressive models, in line with the seminal work of Hamilton (1989). The estimation technique, within a Bayesian framework, is Markov chain Monte Carlo (MCMC), which allows us to jointly estimate all the parameters of the model, including the groups of regions. The idea is to group time series and to pool within clusters to obtain posterior inferences, without an overall pooling being necessary, thus avoiding the heterogeneity bias. This means that, within a panel of time series, only those that display similar dynamic properties and share similar business cycle features are pooled to estimate the parameters, the appropriate grouping being estimated along with the model parameters.

Thus, by using this method a clear gain of efficiency is achieved. Other valuable features of this method are its flexibility, as it admits different specifications, such as autoregressive panels, and the abundant information provided, as the estimation of all the model parameters also includes uncertainty measures. In the next subsection, we describe the details and steps of the estimation process.

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[3] Original data typically have an annual frequency. Even if available, quarterly series are short, not homogeneous across countries and, generally, artificially constructed by interpolating annual data.

[4] Nevertheless, there are some exceptions: Gadea *et al.* (2012) date and build clusters for the Spanish regions and Stock and Watson (2008) identify clusters from the idiosyncratic terms of a dynamic factor model for the US states' housing prices.

[5] Kaufmann (2010) applies this method to analyze the Austrian business cycle using a large set of series.

2.1 Finite Mixture Markov Models estimation process

Let y_{it} be a set of time series from $t = 1, ..., T$ for $i = 1, ..., N$, N being the number of regions which arise from K groups, whereby for each group, $k = 1, ..., K$, we define an econometric model to capture its business cycle with the same parameters, θ. This model is based on the Markov-switching (MS) approach proposed by Hamilton (1989). In the simplest setting, MS models characterize a series through a process of a mean conditioned on a state of nature. The changes in value of this mean allow us to differentiate periods of expansions and recessions. In general, we consider the following process for the growth of the GDP, computed as the first difference of its log:

$$y_{it} = \mu_{i,B_j} + \epsilon_{it} \tag{1}$$

where y_{it} is the log difference of GDP of region i in time t, μ_{i,B_j} is the vector of MS intercepts and $\epsilon_{it}/_{B_j} \sim \mathrm{N}(0, \sigma_i)$ if we consider that the variance of the errors is equal for all states. It is standard to assume that these varying parameters depend on an unobservable state variable B_j that represents the business cycle state and evolves according to an irreducible m-state Markov process, where p_{kj} controls the probability of a switch from state j to state k.

In this framework, we use a classical MS model with 2 states ($j = 1, 2$) that define two possible means, $\mu_{i,1}$ and $\mu_{i,2}$, which are associated with expansion and recession phases, respectively. A 2x2 transition matrix governs regime shifts, where $\xi_{i,11}$ and $\xi_{i,22}$ represent the probability of being in expansion or recession, respectively, and remaining in the same state in the following period; $\xi_{i,12}$ denotes the probability of switching from recession to expansion and $\xi_{i,21}$ is the probability of switching from expansion to recession.[6]

[6] A habitual extension is to introduce dynamics in this basic framework.

As the MS model provides a dating procedure for each region, a methodology for clustering is needed. The first step is to introduce a latent group indicator S_i that denotes to which group y_i belongs for all t. This is,

$$p(y_i|\theta_{S_i}) = \begin{cases} p(y_i|\theta_{S_1}), \ S_i = 1 \\ \ldots \\ p(y_i|\theta_{S_K}), \ S_k = K \end{cases} \tag{2}$$

Notice that the number of groups, the allocation of each region to a given group and the group-specific parameters $\theta = (\theta_1, ..., \theta_K)$ are estimated from the data. We also define a probabilistic model for $P(S_i = k)$.

Combining the MS model for business cycle dating and the finite mixture for clustering, the basic model is specified as follows:

$$y_{it} = \mu_k^G + \delta_{1,k}^G y_{i,t-1} + ... + \delta_{p,k}^G y_{i,t-p} + (I_{kt} - 1)(\mu_k^R + \delta_{1,k}^R y_{i,t-1} + ... + \delta_{p,k}^R y_{i,t-p}) + \epsilon_{it} \tag{3}$$

where y_{it} represents the GDP growth rate of region i in time t and p the order of the autoregressive dynamics. Therefore, μ_k^G and $\delta_{j,k}^G$ for $j = 1, ...p$ are the group-specific effects and μ_k^R and $\delta_{j,k}^R$ the state-specific effects. The group indicator is defined as $S_i = k$ with $k = 1...K$. Periods of expansion (above-average growth periods) are denoted by $I_{kt} = 1$ with intercept μ_k^G and periods of recession (below-average growth periods) are denoted by $I_{kt} = 0$ with intercept $\mu_k^G - \mu_k^R$. We consider that the autoregressive dynamic is different for each group, thus $\delta_{j,k}^G$ and $\delta_{j,k}^G - \delta_{j,k}^R$, $j = 1, ...p$.

Denoting by $\varphi = (\theta, \eta, \xi)$, we estimate the set of state-specific and group-specific parameters θ, the transition matrix $\xi_{k,jj}$, the group probabilities, $\eta = (\eta_1, ..., \eta_K)$ and, implicitly, the number of groups, K. Disturbance terms have unit-specific variances $\epsilon_{it} \sim N(0, \sigma_i^2)$ with $\sigma_i^2 = \sigma^2/\lambda_i$.

This is achieved within the Bayesian framework by applying Markov chain Monte Carlo and data augmentation methods and estimate the joint posterior $p(\varphi, S|y) \propto p(y|\varphi, S)p(S|\varphi)p(\varphi)$ in two steps. First, each time series is classified in one of the K groups by sampling the groups indicator S_i from the posterior distribution $P(S_i = k|y, \varphi)$, and secondly, conditional on known indicators $S = (S_1, ..., S_K)$ the estimation of the parameters is carried out by sampling then from the posterior probabilities $p(\varphi|S, y)$.[7] For estimation purposes, 5,000 draws and non-informative priors are considered.[8] We use independent priors with the hyperparameters recommended by Frühwirth-Schnatter and Kaufmann (2008):[9]

- $\eta_1, ..., \eta_k \sim D(1, ...1)$
- $\sigma^2 \sim G^{-1}(1, 1)$
- $\lambda_i \sim G(4, 4)$
- $\xi_{k,jj} \sim B(3, 1), j = 1, 2$
- $\mu_k^G \sim N(0, 4) \quad \text{and } \mu_k^G - \mu_k^R \sim N(0, 4)$
- $\delta_{l,k}^G \sim N(0, 1)$
- $\delta_{l,k}^G - \delta_{l,k}^R \sim N(0, 1)$
- $l = 1, ..., p$, for $k = 1, ..., K$.

where D denotes a *Dirichlet* distribution; G, a *Gamma* distribution; and B, a *Beta* distribution.

The number of components, K, can be selected through the point-process representation or maximum likelihood. We apply three different criteria to estimate the likelihood function: importance sampling, bridge sampling and reciprocal sampling.

[7]We follow the approach of Frühwirth-Schnatter and Kaufmann (2008).

[8]All the calculations have been done using the Matlab Toolbox provided by Frühwirth-Schnatter (2008) and the specific codes that Silvia Kaufmann kindly shared.

[9]For a more detailed discussion about priors selection in finite mixtures and Markov Switching models, see Frühwirth-Schnatter (2006).

The last issue before classifying the groups is their identification to avoid label-switching problems. In this regard, we use the combination of two restrictions. The first one identifies states by $\mu_k^R > 0$, $\forall k = 1, ..., K$ to ensure that $\mu_k^G > \mu_k^G - \mu_k^R$, that is, the mean in expansions is above the mean in recessions. The second identifies states within each group. In this case, different groups of parameters can be used. This empirical strategy consists of trying the following three alternatives of identification: either $\delta_{j,1}^G < \delta_{j,2}^G < ... < \delta_{j,K}^G$ $\forall j = 1, ..., p$, $\mu_1^R < \mu_2^R > ... < \mu_K^R$ or $\mu_1^G > \mu_1^G > ... > \mu_K^G$. Then, we select the most suitable clustering from a visual inspection of scatterplots and through the ability of the identified model to separate groups unequivocally. The aim is to get the largest possible number of units within one group or another. The units are placed in a group according to their probability, computed using expression 2, which has to be above 0.5.

3 Illustration: European regions

We consider GDP data corresponding to 213 NUTS-2 regions from 16 European countries: Austria, Belgium, Finland, France, Germany,[10] Ireland, Italy, Luxembourg, the Netherlands, Portugal, Spain, Greece, Denmark, Sweden, the UK and Norway. The series cover a period of 32 years, from 1980 to 2011. The source of the data is Cambridge Econometrics.

We estimate different specifications depending on the number of groups $K = 1, 2, 3, 4, 5, 6$ and lags $p = 1, 2$. The three sampling likelihood criteria are considered to select the best model. All of them agree that the preferred model for European regions includes two lags of GDP and identifies five groups, i.e. $p = 2$ and $K = 5$, respectively (see Table 1). The second-best performing models, which are also analyzed to illustrate the performance of the method, consider 4 and 6 groups and 2 lags.

[10]The eastern Landers and Berlin are not included in the analysis because there is no data prior to 1991.

Scatterplots of the MCMC processes for different pairs of parameters are displayed in Figure 1, which shows the posterior draws following a Bayesian estimation for the preferred model $K = 5$ and the other two possible candidates. Each point of the scatterplot offers the location of the draws of the posterior estimated parameters. Different colors represent each cluster of European regions. Clustering is clearer in the model with five groups, whatever the parameters considered, supporting the model selected by the likelihood criteria.

Regarding the identification of groups, we have imposed some restrictions in addition to $\mu_K^R > 0$, $\forall K$, which are detailed in the first column of Table 2. The percentage of regions that are not unambiguously allocated to a group, with a probability greater than 0.5, following these identification restrictions, is presented in the second column of the table for $K = 5$. Notice that considering $\mu_1^G > \mu_1^G > ... > \mu_K^G$ or, equivalently, ordering the clusters from the highest to the lowest growth during an expansion period, we get a classification of almost 100% of the regions.[11]

The probability by region of belonging to each of the five groups is depicted in Figure 2. We assign each region to the group for which its probability of belonging is above 0.5. The probability of being in each group is, in most cases, close to one. The probability of belonging to group five, the one that concentrates most of the regions, is also quite high in many of the regions that are classified in other groups.

Figure 3 depicts some of the main features of the five clusters. The first plot is related to the cyclical phase. We observe that the probability of recession clearly differs among the clusters, the highest probability corresponding to cluster one and the lowest in cluster five. The second and the third plots represent economic conditions. The lowest weight of the industrial sector is in cluster one and is clearly below the average of all the European regions. Cluster one also displays the highest unemployment rate while the rest of the clusters are all below the European average. In order to get a geographical classification of the regions, in the last plot we

[11]Figures for the other parameters are available upon request.

define groups of countries[12] and compute the percentage of regions in each cluster belonging to each group. It seems that clusters one, two and three are related to geographical criteria, while clusters four and five include regions of different groups of countries (See Bandres, *et al.*, 2017).

In order to document the business cycle estimates of each of the five clusters and the European business cycle as a whole, we present Figure 4. We observe that cluster five is representative of the European business cycle. The timing of the business cycle is different in the rest of the clusters, especially cluster one, since they undergo more recessionary periods.

On the whole, we can confirm the ability of the FMMM to properly capture the variability of the regional cycles.

4 Concluding remarks

This letter illustrates the usefulness of FMMM for estimating and clustering regional business cycles. This method allows us to jointly estimate the parameters associated with the business cycles and to cluster regions with similar characteristics, overcoming the weaknesses of other techniques when applied to regional data. An empirical application to a set of European regions shows the suitable performance of this methodological framework. A more detailed analysis of the estimated parameters and the features characterizing each cluster would give us valuable information of the European business cycle.

[12]Specifically, "Central countries" (Belgium, Germany, France, The Netherlands, Luxembourg and Austria), "Nordic countries" (Denmark, Sweden, Norway and Finland), "Mediterranean countries" (Greece, Italy, Portugal and Spain) and "British Isles" (Ireland and the UK). Gadea, *et al.* (2017a) define a similar grouping of countries.

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5 Tables

Table 1: Log-marginal likelihood of different Markov Switching model specifications with group-specific autoregressive coeffients

Model K,p	Importance sampling	Bridge Sampling	Reciprocal Sampling
1,1	-14561.98	-14561.28	-14561.98
1,2	-13986.91	-13986.20	-13986.90
2,1	-13986.91	-13986.20	-13986.90
2,2	-13948.44	-13948.00	-13948.71
3,1	-14430.85	-14429.66	-14430.89
3,2	-13795.62	-13794.28	-13795.33
4,1	-13948.44	-13948.00	-13948.71
4,2	-13778.06	-13774.50	-13775.67
5,1	-14361.92	-14419.50	-14419.22
5,2	**-13737.03**	**-13724.26**	**-13730.18**
6,1	-13795.62	-13794.28	-13795.33
6,2	**-13748.13**	**-13743.97**	**-13748.25**

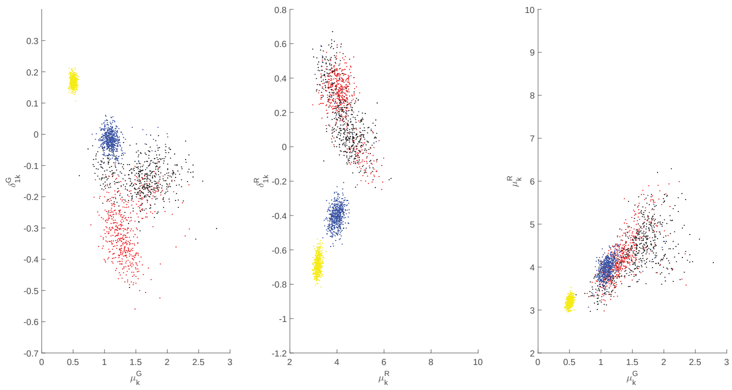
Notes: The highest values are indicated in bold.

Table 2: Identification strategy

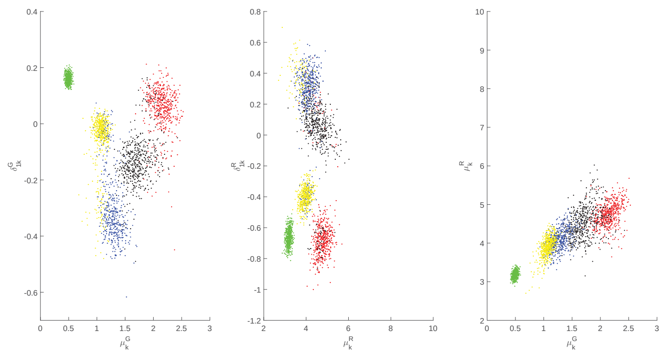
$\mu_K^R > 0, \forall K$	% of non-assigned regions
$\delta_{j,1}^G < \delta_{j,2}^G < ... < \delta_{j,K}^G \ \forall j = 1, ..., p$	0.01
$\mu_1^R < \mu_2^R > ... < \mu_K^R$	0.24
$\mu_1^G > \mu_1^G > ... > \mu_K^G$	0.00

Notes: The first column indicates the identification restrictions used in combination with the restriction $\mu_K^R > 0$, $\forall K$. The second column indicates the percentage of regions that are not unambiguously allocated to a group.

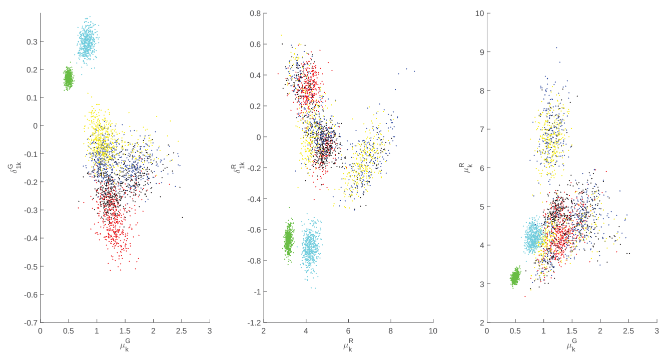
6 Figures



(a) K=4, p=2



(b) K=5, p=2



(c) K=6, p=2

Figure 1: Scatterplots of the MCMC draws

Notes: From left to right, scatterplot MCMC draws of simulated group-specific parameters μ_k^G against $\delta_{1,k}^G$, scatterplot of simulated state-group specific effects μ_k^R against $\delta_{1,k}^R$ and scatterplot of simulated group-specific parameters μ_k^G against μ_k^R. The scatterplots display values for k=1,...,K.

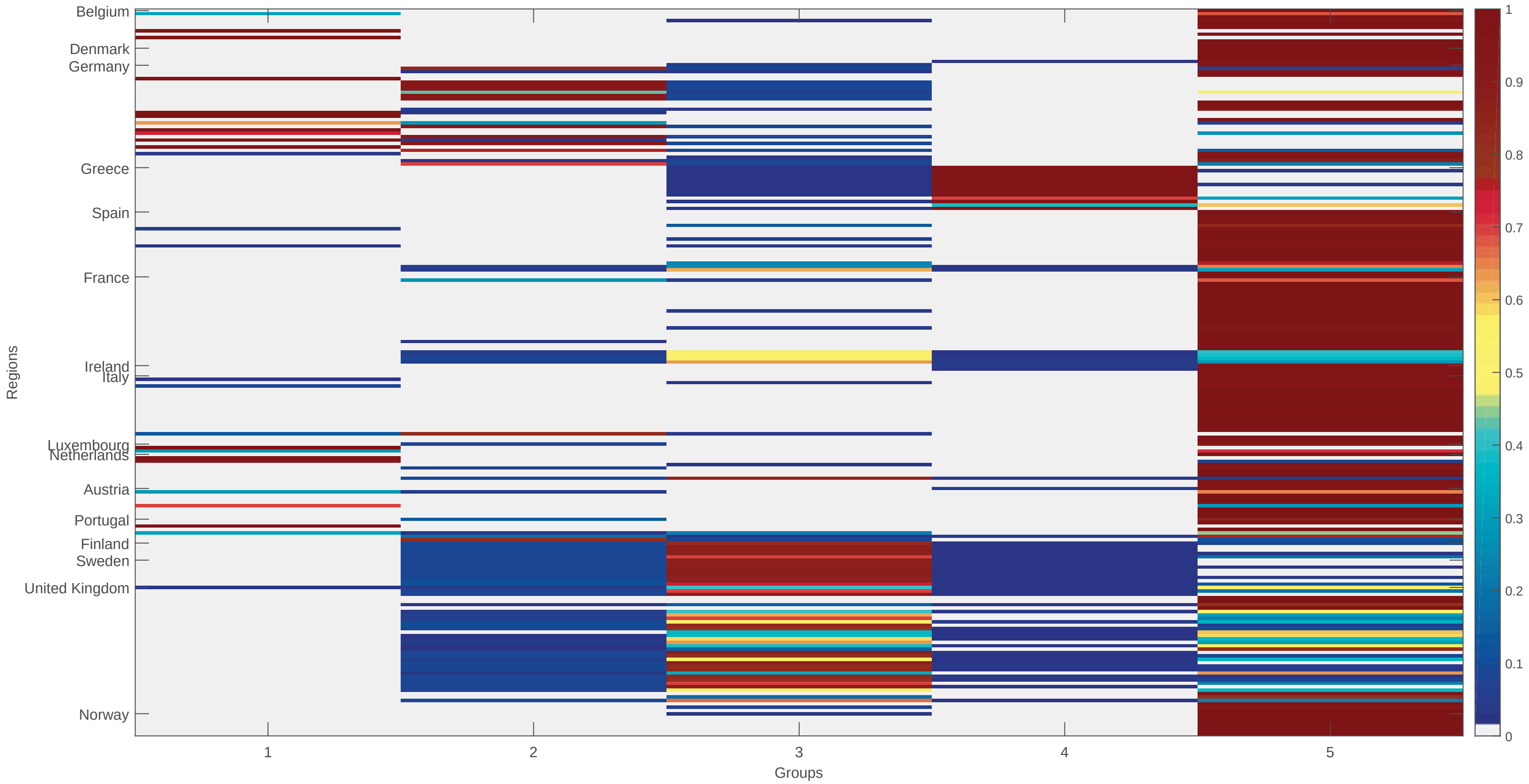


Figure 2: Probability by region of being in each group

Notes: This figure shows the probability of each region belonging to each group. The lowest probability of being in a group is illustrated with the lightest colors, while the highest probability is represented in brown. The regions belonging to each country are on the y-axis.

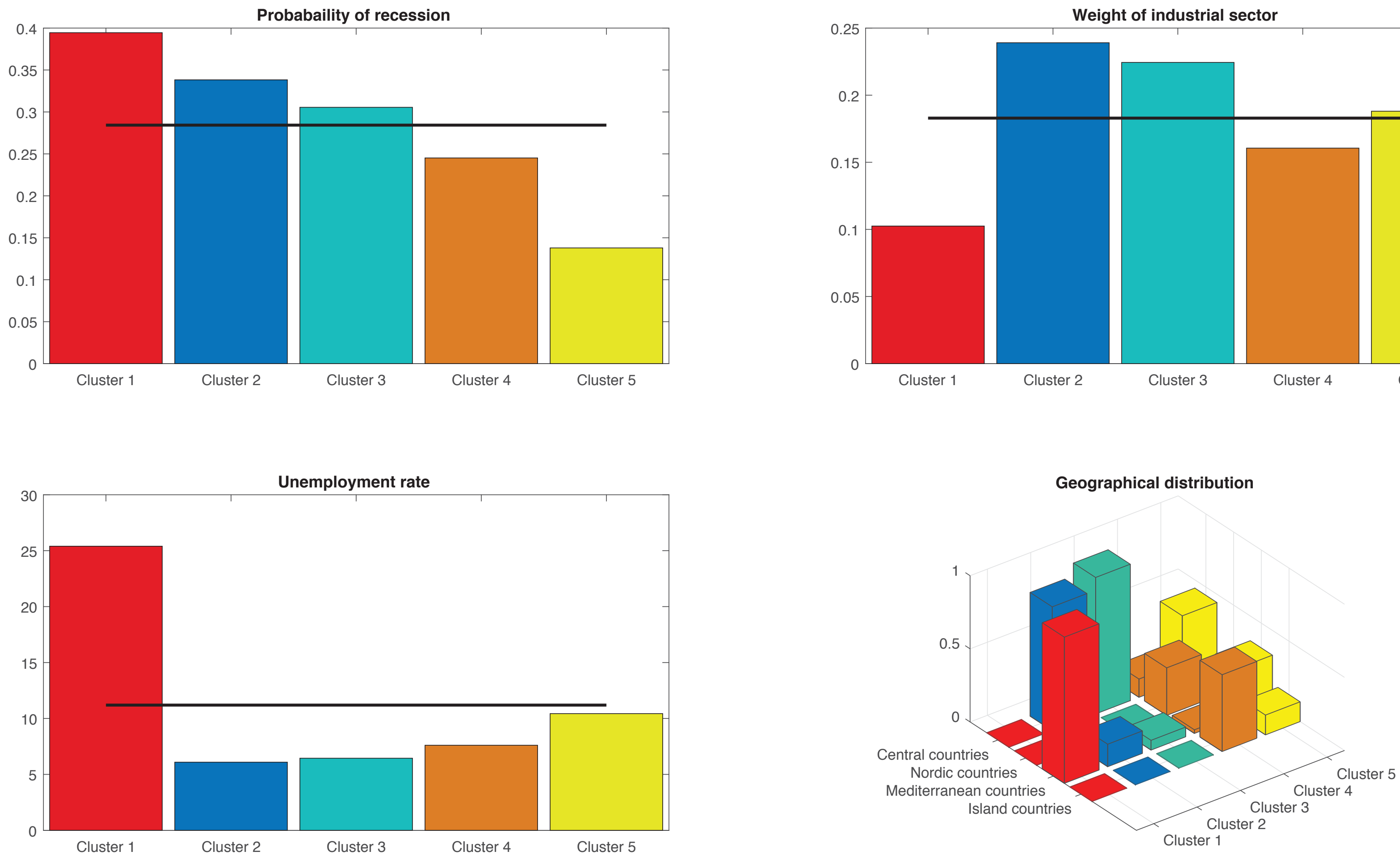


Figure 3: Some features by cluster

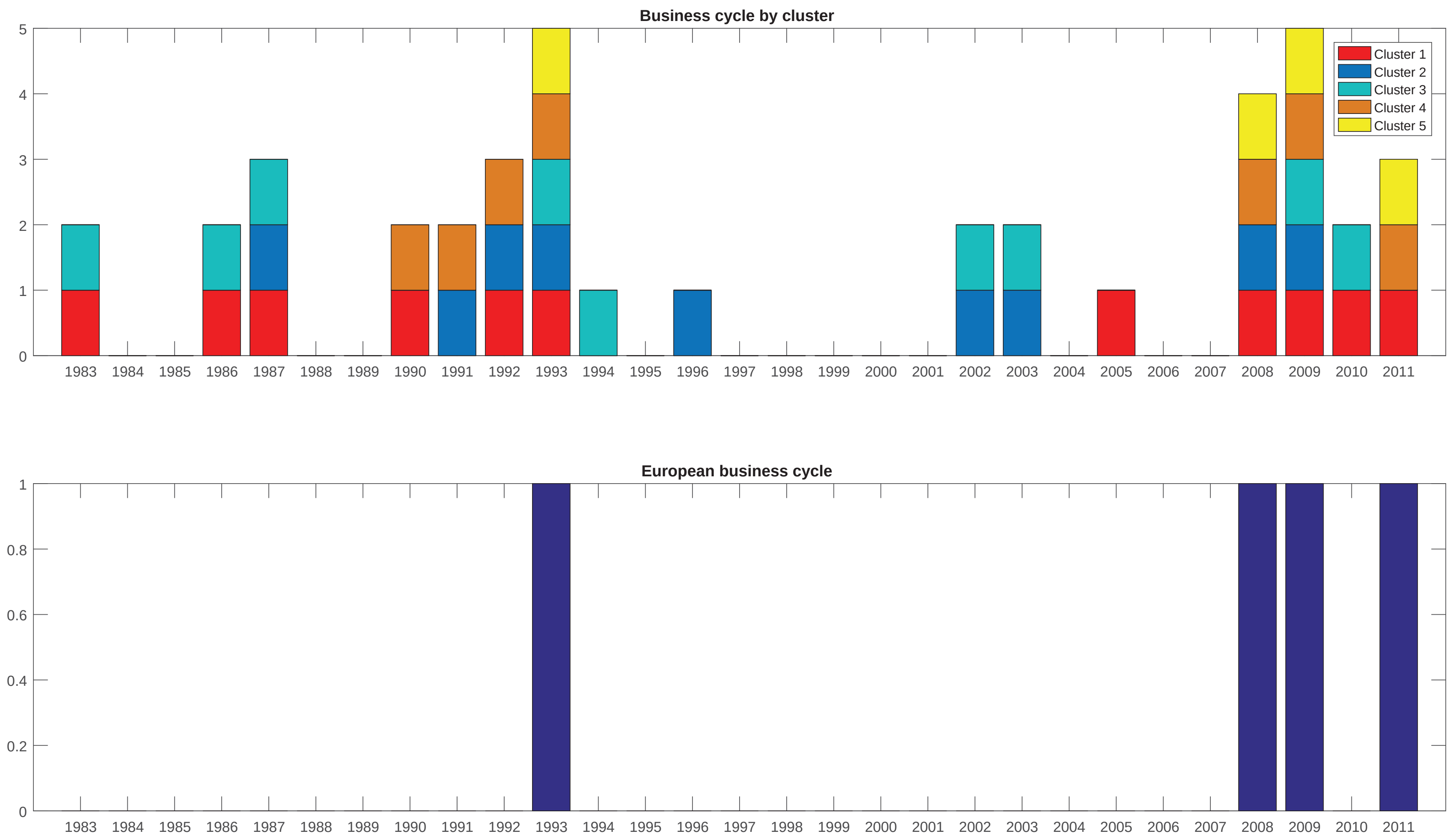


Figure 4: Business cycle estimates

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