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Business cycle patterns in European regions ^{*}

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Abstract

The aim of this paper is threefold. First, we analyze the comovements of the business cycles of European regions. Second, we date these business cycles, for the first time in the literature, and identify clusters of regions with similar business cycle behavior, using Finite Mixture Markov models. Third, we develop a new index to measure within-country homogeneity. We find that comovement among regions is, on average, quite low, although it increased during the convergence process prior to the euro cash changeover and after the onset of the Great Recession. We identify five different groups of European regions. We also find heterogeneity in the size of border effects.

JEL classification: C32, E32, R11

Keywords: business cycle dating, comovements, clusters, regions, Finite Mixture Markov models.

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1 Introduction

Regional considerations have been highly relevant for European institutions since the establishment of the European Economic Community and, indeed, there are regional policies aimed at diminishing interregional differences (the 'Cohesion Policy').¹ are employed. For instance, around a third of the total EU budget during the period 2014-2020 corresponds to the Cohesion Policy.

Valuable policy lessons can be learned from the study of regional features. Implementing national economic policies could bring about undesirable distortions in some regions and slow down their convergence processes. This issue is particularly important because GDP evolution is very different across European regions, as will be shown in this paper. Furthermore, several regions with different business cycle features, which may require policies adapted to their territorial specificities, are identified. From a EU perspective, the design of cohesion policies that increase regional competitiveness and foster economic growth and employment is very important (see European Commission, 2017). From an individual country perspective, in countries where public revenue and expenditure decisions have an important regional dimension, such as Germany and Spain, fiscal policy could be used to reduce within-country regional disparities.

In the existing literature, much effort has already been devoted to country analyses of the European business cycles. For instance, many papers have analyzed the business cycles of European Monetary Union (EMU) countries and the synchronization among them.² However, it has to be borne in mind that analyses at the country level may well hide very different regional cyclical developments. Studying the regional dimension of business cycles is therefore important to uncover the heterogeneity hidden in country analyses, as, e.g., Ramajo et al. (2008) show for the European regions, Park and Hewings (2012) for the US states, Hayashida and Hewings (2009) for Japan and Gadea et al. (2012) for Spain. Unfortunately, in spite of the importance of studying regional business cycles in Europe, the focus of the scant number of existing papers has been mainly on the synchronization of short-term fluctuations in economic activity.³

Against this framework, the aim of this paper is threefold. First, we analyze the comovements of the business cycles of European regions. Second, using Finite Mixture Markov models, to compute regional business cycle datings that allow us to identify clusters of regions that show similar business cycle features. Third, to develop a new index to measure within-country homogeneity (border effects).

¹http://ec.europa.eu/regional_policy/en/policy/what/investment-policy/

²See De Haan et al. (2008) for a survey.

³See Fatas (1997), Acedo-Montoya and de Haan (2008), Barrios et al. (2003) and Clark and van Wincoop (2001). Marino (2013) uses dynamic factor models. Ozyurt and Dees (2015) study the determinants of economic performance. Gadea et al. (2017a) combine regime-switching models and dynamic model averaging to measure time-varying synchronization. See Bandres et al. (2017) for a review of this literature.

Our analysis contributes to the existing literature in several ways. First, while there are institutions that establish a chronology of recessions and expansions for the euro area as a whole and for individual countries, no business cycle dating has been carried out for European regions so far.⁴ In this paper, we use a sophisticated methodology that dates the business cycles of regions and identifies clusters among them. Moreover, for the first time in the regional business cycle literature, we use Finite Mixture Markov models (Frühwirth-Schnatter and Kaufmann, 2008). This methodology, which combines clustering techniques and Markov Switching models, allows us to overcome some data limitations and technical difficulties that arise in capturing business cycles with heterogeneous data. In contrast, the existing literature, typically employs very simple methodologies such as computing correlations of different measures of regional economic activity with respect to the country or to the European business cycle.

Second, some of the regional papers identify a border effect, regions belonging to the same country being more synchronized than regions belonging to different countries. Chung and Hewings (2015) suggest that identifying national elements is helpful to evaluate the relationship among regions. However, the literature has so far failed to provide a consensus on the relative importance of borders. On the basis of our methodology, we propose a new index to measure within-country homogeneity or border effects, that takes into account both the regional business cycle datings and the number of regions of each country.

Third, we employ a more comprehensive dataset than in the previous literature, both in terms of its temporal and geographical dimensions, and we use GDP as the measure of economic activity. On the temporal dimension, the existing literature only covers the period prior to the Great Recession and the sovereign debt crisis, two events that may have significantly changed business cycle synchronization in Europe.⁵ In this paper, we fill this gap by analyzing the evolution of regional business cycles in Europe and the comovements among them for a longer period, covering both events. On the geographical dimension, in this paper, we work with 213 NUTS 2 regions. Considering NUTS 2 regions is highly important because regions eligible for support from the Cohesion Policy are defined at the NUTS 2 level. This is in contrast with most of this literature, which considers a much less detailed geographical breakdown.

The main findings of our paper are the following. First, we find that regional growth rates are quite heterogeneous and the spatial correlation among them is quite low during the whole sample. Second, interestingly, we find a progressive increase of summary measures of correlation during the convergence process towards the creation of the euro area and a sharp

⁴Applied to the US states, Hamilton and Owyang (2012) develop a framework for inferring common Markov-switching components in a panel data set with large cross-sectional and time-series dimensions and Owyang et al. (2005) apply a regime-switching model to state-level coincident indices to characterize state business cycles.

⁵The Great Recession was very costly in terms of wealth due to its severity, its duration and the fact that it was global. The severity of this episode, together with the subsequent slow pace of the recovery, has rekindled interest in business cycle analysis. See Gadea et al. (2017b).

rise of comovements among regions during the Great Recession. Third, we identify five different groups of European regions that share different business cycle characteristics. Fourth, we identify sizable border effects, namely, the degree of homogeneity of regional business cycles within countries is quite different.

The rest of the paper is organized as follows. In Section 2, we present the Finite Mixture Markov models methodology and the dataset used in this paper. In Section 3, we report the main results of our paper. The final section concludes.

2 Data and methodology

Business cycle analysis is usually carried out at the national level using long quarterly or monthly samples and datings are obtained with the Bry and Boschan (1971) algorithm and the Markov Switching models (Hamilton, 1989). In contrast, regional data are available for relatively short samples with an annual frequency. Our paper uses Finite Mixture Markov models that allow us to deal with technical difficulties that arise in capturing business cycles with short samples and heterogeneous data. In this section, we describe our dataset and the methodology we employ to establish a regional business cycle dating chronology for the European regions and to identify clusters of regions that share common features.

2.1 Data

The availability of regional data on a high frequency basis and for a long span is scarce. Therefore, to analyze regional business cycles, we employ annual real GDP data, as quarterly data are not available.⁶ It has to be acknowledged that annual data are more reliable to establish robust facts about real economic activity in spite of the loss of information on short-term dynamics.

The nomenclature of territorial units for statistics (NUTS) is the territorial breakdown for compiling regional accounts in the EU.⁷ In this study, we consider 213 NUTS2 regions corresponding to 16 European countries, namely, the 12 euro area (EA12) member states [Austria (AT), Belgium (BE), Finland (FI), France (FR), Germany (DE), Ireland (IE), Italy (IT), Luxembourg (LU), the Netherlands (NL), Portugal (PT), Spain (ES) and Greece (EL)], 3 EU member states [Denmark (DK), Sweden (SE) and the UK (UK)] and Norway (NO), which is not a member state of the EU. The series are available from 1980 to 2011.⁸ This dataset is the most comprehensive in terms of regional coverage that has been used in this literature.

⁶Even if available, quarterly data are short series, not homogeneous across countries and, generally, constructed by interpolating annual data. See Parks and Hewings (2012) for a review of the role of data frequency.

⁷We use the NUTS 2013 classification which lists 98 regions at NUTS1 level, 276 regions at NUTS2 level and 1,342 regions at NUTS 3 level. More details in <http://ec.europa.eu/eurostat/web/nuts/overview>.

⁸Regarding Germany, the eastern Landers and Berlin are not included in our analysis given that we do not have data prior to 1991.

On the one hand, we analyze, for the first time, the possible effect of the Great Recession and the sovereign debt crisis on the regional business cycle of the European countries. On the other hand, we employ regions at the NUTS2 level, which are the geographical units eligible for support from the Cohesion Policy. The source is Cambridge Econometrics.

2.2 Methodology

The use of Finite Mixture Markov models, developed by Frühwirth-Schnatter (2006) and Frühwirth-Schnatter and Kaufmann (2008),⁹ is suitable for analyzing regional business cycles, as shown by Gadea et al. (2018). This methodology has several advantages over other techniques: it not only overcomes some difficulties that arise in capturing business cycles with short samples and heterogeneous data, but also allows us to date the turning points of the business cycle of the regions and cluster them according to their cyclical features. With this model-based clustering approach for multiple time series, we can jointly estimate all the parameters of the model, including the number and composition of groups of regions. One alternative would be to use a two-stage procedure, that is, to date regional business cycles and then, based on these results, to build clusters, with a subsequent loss of information.

Finite Mixture Markov models avoid the heterogeneity bias by grouping time series and pooling them within clusters, enabling posterior inferences, without an overall pooling. This means that only the series that show similar dynamic properties and similar cyclical features are pooled to estimate the parameters.

Let y_{it} be a set of time series from $t = 1, \dots, T$ for $i = 1, \dots, N$, N being the number of regions which arise from K groups, so that for each group, $k = 1, \dots, K$, 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), which aims to characterize a series through a process of a mean conditioned on a state of nature. Changes in this mean allow us to identify expansions and recessions. We consider the following process for the GDP growth, computed as the first difference of its log:

$$y_{it} = \mu_{i,B_j} + \epsilon_{it} \quad (1)$$

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 $\epsilon_{it}/B_j \sim N(0, \sigma_i)$ if we consider that the variance of the errors is the same 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} denotes the probability of a switch from state j to state k .

We use a classical MS model with 2 states ($j = 1, 2$) that define two possible means, $\mu_{i,1}$ and

⁹Kaufmann (2010) applies this method to analyze the Austrian business cycle using a large set of series.

$\mu_{i,2}$, 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.

The methodology for clustering is as follows. A latent group indicator S_i that denotes to which group y_i belongs for all t is introduced. That is,

$$p(y_i|\theta_{S_i}) = \begin{cases} p(y_i|\theta_{S_1}), & S_i = 1 \\ \dots & \\ p(y_i|\theta_{S_K}), & S_i = K \end{cases} \quad (2)$$

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

Having combined the MS model for business cycle dating and the finite mixture for clustering, the basic model is the following:

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

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 $j = 1, \dots, p$ 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 $k = 1 \dots K$. 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 $\delta_{j,k}^G - \delta_{j,k}^R$, $j = 1, \dots, p$. Defining $\varphi = (\theta, \eta, \xi)$, we estimate the set of state-specific and group-specific parameters θ , the transition matrix $\xi_{k,jj}$, the group probabilities, $\eta = (\eta_1, \dots, \eta_K)$ and, implicitly, the number of groups, K . Disturbance terms have unit-specific variances $\epsilon_{it} \sim N(0, \sigma_i^2)$ with $\sigma_i^2 = \sigma^2/\lambda_i$.

The estimation technique, within a Bayesian framework, is Markov chain Monte Carlo. Specifically, each time series is, firstly, classified in one of the K groups by sampling the group indicator S_i from the posterior distribution $P(S_i = k|y, \varphi)$, and secondly, conditional on known indicators $S = (S_1, \dots, S_K)$, the estimation of the parameters is carried out by sampling them from the posterior probabilities $p(\varphi|S, y)$. For estimation purposes, 5,000 draws and non-informative priors are considered.¹⁰ We use independent priors with the hyperparameters

¹⁰We follow the approach of Frühwirth-Schnatter and Kaufmann (2008). All the calculations have been done using the Matlab Toolbox provided by Frühwirth-Schnatter (2008) and the specific codes kindly provided by S. Kaufmann.

recommended by Frühwirth-Schnatter and Kaufmann (2008).¹¹

The number of components, K , is selected considering four methods: the point-process representation and three maximum likelihood criteria. To avoid label-switching problems, we use a combination of two restrictions. The first one assumes that the mean in expansions is higher than the mean in recessions. The second one identifies states within each cluster using different groups of parameters. See Gadea et al. (2018) for details. Each region is placed in one and only one cluster, because the probability of being assigned to this cluster, calculated using expression 2, has to be above 0.5.

3 Empirical results

In this section, we examine our regional dataset and analyze the comovements of the regions during the sample. Then, we obtain, for the first time in the literature, a business cycle dating of the European regions and classify them into different clusters. Finally, on the basis of the previous results, we propose a new index to measure within-country homogeneity.

We have the following hypotheses: (H_1) we expect that the Great Recession combined with the European debt crisis have had an impact on the dynamics of comovements; (H_2) given the wide set of data, we expect to find several clusters among the European regions; (H_3) given that the neighboring regions tend to be more similar, we expect some of the clusters to be geographically located and; (H_4) given the idiosyncrasy within each country, we expect border effects to be sizable.

3.1 Dynamics of European regional business cycles

To get an overview of our regional data, which consists of 213 regions and 32 years, we calculate the kernel density of the regional growth rates for each year of our sample, which is displayed in the upper panel of Figure 1 and shows great heterogeneity in GDP growth rates. This high degree of variability, across both space and time, could be due to the presence of outliers. In order to remove them and maintain the signal of cyclical phases, we have linearly interpolated the observations that are four times or more above the standard deviation over the median of each regional time series. Using this methodology, we identify six outliers.¹² The lower part of Figure 1 shows the density once the outliers have been removed.

¹¹ $\eta_1, \dots, \eta_k \sim D(1, \dots, 1)$; $\sigma^2 \sim G^{-1}(1, 1)$; $\lambda_i \sim G(4, 4)$; $\xi_{k,jj} \sim B(3, 1)$, $j = 1, 2$; $\mu_k^G \sim N(0, 4)$ and $\mu_k^G - \mu_k^R \sim N(0, 4)$; $\delta_{l,k}^G \sim N(0, 1)$; $\delta_{l,k}^G - \delta_{l,k}^R \sim N(0, 1)$; $l = 1, \dots, p$, for $k = 1, \dots, K$, where D denotes a *Dirichlet* distribution; G, a *Gamma* distribution; and B, a *Beta* distribution.

¹²They correspond to the Spanish regions of Ceuta and Melilla (ES63 and ES64) in 1985, Burgenland in Austria (AT11 in 1995), the Portuguese regions of Norte (PT11) in 1990 and Alentejo (PT18) in 1988 and Ovre Norrland in Sweden (SE33) in 2009.

After eliminating outliers, we analyze the patterns of comovements in the regional series. The upper part of Figure 2 represents regional GDP growth rates (blue lines) together with the median and the first and the third quartiles (red lines) of the series. In spite of the great number of series and their high variability, we can observe quite a smooth cyclical path in which the most outstanding event is the Great Recession.

In order to analyze how the series move together over the sample, we compute Moran's modified statistic, following Stock and Watson (2008), which summarizes the possible time-varying comovements among GDP growth rates.

The measure is based on Moran's spatial correlation index and captures the comovements over time across all the regions through the rolling cross-correlation of logarithmic growth rates. It has the following expression:

$$\begin{aligned}\widehat{I}_i &= \frac{\sum_{i=1}^N \sum_{j=1}^{i-1} \widehat{cov}(y_{it}, y_{jt}) / N(N-1)/2}{\sum_{i=1}^N \widehat{var}(y_{it}) / N} \\ \widehat{cov}(y_{it}, y_{jt}) &= \frac{1}{k} \sum_{s=t-int(k/2)}^{t+int(k/2)} (y_{is} - \overline{y_{it}})(y_{js} - \overline{y_{jt}}) \\ \widehat{var}(y_{it}) &= \frac{1}{k} \sum_{s=t-int(k/2)}^{t+int(k/2)} (y_{is} - \overline{y_{it}})^2 \\ \overline{y_{it}} &= \frac{1}{k} \sum_{s=t-int(k/2)}^{t+int(k/2)} y_{is}\end{aligned}\tag{4}$$

where y_{it} is the real GDP growth of region i in time t , $k = 5$ is the rolling window and $N=213$.

The results are displayed in the bottom part of Figure 2. We observe that the synchronization of comovements among regions is slightly above 0.2, on average. The time series of this index shows that spatial correlation progressively increased during the convergence process towards the European Monetary Union and increased substantially as a consequence of the Great Recession, reaching a value of 0.7,¹³ confirming H_1 . If we compute this measure for the European countries, we find that the synchronization of comovements is around 0.5, on average, much higher than for European regions, reflecting the relevance of region-specific shocks. Using country data, we also find a mild upward trend, briefly interrupted after the introduction of the euro, and a sharp increase at the time of the Great Recession.

¹³Gadea et al. (2017a) obtain similar conclusions using a methodology that combines Markov Switching models and dynamic model averaging.

3.2 Dating and clustering European regional business cycles

To obtain regional business cycle datings and to determine groups of regions, we estimate Finite Mixture Markov models, as previously described in Section 2. To select the best model, we estimate the log-marginal likelihood of different Markov Switching specifications considering different parameters for each group. Three sampling likelihood criteria are considered: importance sampling, bridge sampling and reciprocal sampling. All three methods agree that the preferred model for European regions includes two lags of GDP and identify five groups, i.e. $p=2$ and $K=5$, respectively. Furthermore, by analyzing the distribution of the posterior draws of the Markov Chain Monte Carlo processes for the different parameters following a Bayesian estimation, we are able to distinguish five clear clusters of European regions, confirming the previous model specification.

Regarding the identification of groups, we consider different identification criteria and choose the one that maximizes the percentage of regions unequivocally assigned to a group. We have imposed three restrictions in addition to $\mu_K^R > 0, \forall K$. The first identifies clusters by setting a restriction on the autoregressive parameters, that is, to order the groups from the lowest to the highest persistence of expansionary phases ($\delta_G(1) < \delta_G(2) < \dots < \delta_G(K)$), the second classifies groups from the lowest to the highest growth rates in recessions ($\mu_R(1) < \mu_R(2) < \dots < \mu_R(K)$) and the third orders the clusters from the highest to the lowest growth during expansions ($\mu_G(1) > \mu_G(2) > \dots > \mu_G(K)$). We find that considering $\mu_G(1) > \mu_G(2) > \dots > \mu_G(K)$ we get a classification of almost 100% of the regions. We assign each region to the group for which its probability of belonging is above 0.5.¹⁴ We obtain that the probability of being in each group is, in most regions, close to one.¹⁵ However, there are some regions (mainly, French and British), located in the fourth group, that have a similar probability of being in the fifth.

The geographical distribution of regional business cycles into different groups is displayed in Figure 3. The first group is made up of all the Greek regions but one (12 regions in total), so we refer to it as *the Greek group*; in the second group, we find mostly German regions (11) -half of them, in the south of the country-, plus one Italian and one Portuguese region (13 regions in total), and we label it *the southern Germany group*; the third group includes some German (8) -located, mainly, in the northwest of the country-, Belgian (2) and Dutch (3) regions as well as one Austrian and one Portuguese region (15 regions in total), which we call *the core group*; the fourth group contains most of the UK regions (21), all the Swedish and Finnish regions (8 and 5, respectively), one Dutch region, one Spanish region and the four French overseas regions (40 regions in total), and we call it *the northern group* and, finally, the fifth group is the largest and is composed of the remaining regions (132 regions in total), which we refer to as *the largest*

¹⁴In fact, the only region with a probability of being assigned below 0.5 is the Portuguese region of Alentejo (PT18). Its most likely location (probability of 0.44) is in the fifth group.

¹⁵We list the probabilities of belonging to each group of all the regions by country in Appendix 1.

group. This classification seems to be related, at least partially, with the geographical location, as expected in H_3 . In the last column of Table 1, we note that the number of regions clearly differs among groups, the largest one comprising more than 60% of the total number of regions.

Table 1 summarizes the posterior estimates for the parameters of interest of the chosen model specification for the European regions. It can be observed that intercepts during expansions and recessions ($\mu_{S_i}^G$ and $\mu_{S_i}^G - \mu_{S_i}^R$, respectively) clearly differ among groups. There are different mean growth rates in expansion, as can be seen from the $\mu_{S_i}^G$ values of the five groups, whereas the mean growth rates in recession, $\mu_{S_i}^G - \mu_{S_i}^R$, are broadly similar across groups. The growth rates for each group during expansionary phases are the following: 2.15% in the Greek group, 1.73% in the southern Germany group, 1.26% in the core group, 1.07% in the northern group and 0.49% in the largest group. Meanwhile, the mean growth rates during recessionary phases are -0.45% in the Greek group, -1.07% in the southern Germany group, -1.57% in the core group, -1.77% in the northern group and -2.21% in the largest group.

For a better understanding of the features characterizing each group, in Figure 4, we present the quartiles of the GDP growth distributions, the minimum and maximum values of each series and their outliers. We observe that the Greek group has the lowest average GDP growth and the highest variance. The other groups are quite homogeneous with regard to their average growth rates and variability.¹⁶

Additionally, the mean persistence of the states $I_t = 1$ and $I_t = 0$ ($\xi_{11}^{S_i}$ and $\xi_{00}^{S_i}$, respectively), that is, the probability of being in expansion (recession) conditional upon being in expansion (recession) in the previous period is quite similar among the groups. The values of the autoregressive parameters show that the series are far from non-stationary in all cases. However, we observe that the series are more persistent during periods of economic recovery than during periods of economic slowdown. It should be noted that expansionary periods are more persistent in the northern and the largest groups than in the others, the least persistent recoveries being in the Greek group. The persistences for each group of expansionary phases are 0.7 in the Greek group, 0.73 in the southern Germany group, 0.79 in the core group, 0.83 in the northern group and 0.86 in the largest group. The persistences of recessionary phases are 0.56 in the Greek group, 0.55 in the southern Germany group, 0.57 in the core group, 0.67 in the northern group and 0.57 in the largest group.

The probability of being in recession is estimated separately for each of the five groups in Figure 5. It should be pointed out that there are two recessionary periods that are common to the five groups, namely, that at the beginning of the nineties and that during the Great Recession. The deceleration at the beginning of the noughties mainly affected the regions in the southern Germany and the core groups (and, to a lesser extent, the Greek group). The

¹⁶However, the core group, has one atypical region and the largest group has the highest number of outliers, five, that all belong to different countries.

probability of being in recession of the Greek group, the southern Germany group and the core group also reflects an additional period of growth slowdown in the mid 1980s, after the economic instability of the 70s that was due to the different oil price shocks.

We compute a recession diffusion index, defined as the percentage of clusters in recession, to see the evolution of the number of groups that are in recession in each year of our sample (Figure 6). The index confirms the two above-mentioned common recessionary shocks, one at the beginning of the nineties and the other associated with the Great Recession. Other recessionary periods only affected specific groups. We do not observe any pattern in cluster similarity of business cycle datings after the introduction of the euro.

The detailed business cycle of each group is depicted in Figure 8, representing recessions and expansions ($I_t = 0$ and $I_t = 1$, respectively). There are some remarkable differences in the cyclical performance of the different groups.

1. Regions belonging to the Greek group are in recession for a large part of the sample (eleven years out of thirty one), the southern Germany and the core groups underwent downturns in nine years of the sample, the northern group was in recession during eight years and regions in the largest group suffered only four recessionary years.
2. All the groups underwent the Great Recession, but with a different severity. The greatest intensity is registered in the Greek group, in which the recession began in 2008 and continued without interruption until 2011, the last year of our sample. However, in the remaining groups, either the Great Recession ended earlier or it hit again after a short expansion, causing a double dip. Furthermore, in the core group, it arrived a year later (2009) than in the other groups.
3. The crisis at the beginning of the nineties is also present in all the groups, but with a different timing and duration in each of them. The longest duration of the recession was in the southern Germany and the northern groups (four years) and the shortest in the largest group, where it lasted for one year.
4. The deceleration of the beginning of the noughties appeared in the second and third groups, which include most of the German regions, during 2002 and 2003, although the Greek group also experienced a brief recession in 2005. The deceleration of 2001 did not affect regions belonging to the northern and the largest groups.
5. We find important differences in the aftermath of the oil crises, that is, during the slowdown of the mid-eighties. The Greek and the core groups suffered a recession in the first year of the sample. After 1985, one or two years of slowdown are also observed in the Greek, the southern Germany and the core groups.

6. There are fewer recessions in the northern and the largest groups than in the rest of the groups. This might be due to their economic size, given that region-specific shocks could play a less relevant role in driving the business cycle.

Finally, the stylized features characterizing the intensity of the cyclical phases of the five groups of European regions can be summarized as follows.

1. The two phases of the business cycle are clearly distinguished in all the groups, although the dispersion across groups is higher during periods of recovery than during periods of recession, in line with regional literature.¹⁷ The growth rate during expansion ranges from 0.49% in the largest group to 2.15% in the Greek group, while the growth rate during recessions ranges from -2.84% in the northern group to -2.6% in the Greek group. In order to interpret these figures, it has to be borne in mind that regions in the Greek group are in recession most of the time so, in spite of the high growth rate during expansion, they do not have a better performance in terms of accumulated growth. On the contrary, regions in the largest group only experience a recession during four years and are especially intense during the three years of the Great Recession.
2. The mean persistence of the states is higher during expansions than during recessions and both are quite homogeneous among the groups. The persistence, i.e., the probabilities of remaining in each state, range from 0.7% in the Greek group to 0.86% in the largest group during recoveries and from 0.55% in the southern Germany group to 0.67% in the northern group during recessions.

3.3 Testing homogeneity within country

The literature has paid attention to whether business cycles across regions of the same country tend to be more correlated than business cycles across regions of different countries or not, a phenomenon called "border effect". Some potential explanations for the existence of this border effect are sectoral specialization (since regions within a country tend to have more similar production structures than regions in different countries), trade (because it is related to distance, culture, language and institutions), monetary policy (to the extent that monetary policy shocks are a source of business cycles, one would expect that a single policy would lead to higher business cycle synchronization)¹⁸ and fiscal policy (since decentralized fiscal systems could help to reduce economic disparities and, thus, increase synchronization). There is lack

¹⁷Chung (2016) finds more coordination during periods of recession for the US states. Also for the US states and cities, Owyang et al. (2005 and 2008) further investigate the determinants of the average growth rates of the two cyclical phases.

¹⁸This explanation is less clear due to the fact that common policies do not allow flexibility to dampen country-specific shocks.

of consensus in the literature about the effect of national borders. For instance, Clark and van Wincoop (2001) and Acedo-Montoya and de Haan (2008) support the existence of border effects, whereas Fatas (1997) finds low within-country correlations.¹⁹

To get a better understanding of the spatial dimension of European regional synchronization, we propose a new measure to test the homogeneity of regional business cycles associated with each country using the outcomes of Finite Mixture Markov models. This allows us to identify the countries containing regions with more or less homogeneous business cycles. We propose an index I_c of *Regional business cycle homogeneity* that it is computed for each country c , as follows:

$$I_c = \sum_{i=1}^{\tilde{K}-1} \sum_{j=1}^{NR_c} |P_j - 1/K| \overline{p\hat{r}}_i \quad (5)$$

- where P_j is a dummy variable that takes value 1 if a region belongs to group i and 0 otherwise, NR_c being the number of regions in country c .
- $\widehat{p\hat{r}}_i$ is the mean of the probabilities of the regions in group i and \tilde{K} represents the K clusters ordered from low to high.

The closer the value of the index is to 0, the higher the degree of heterogeneity, while the closer the value is to 1, the higher the degree of homogeneity. This index is based on the results of the clustering procedure applied to the regional economic cycles. It combines information on the number of regions of a country that are within the same cluster, and the probability of each region belonging to that cluster. Therefore, it is different from other regional measures of synchronization, such as a standard deviation of regional growth rates, that do not take into account the dating of the business cycle. Consequently, this new measure yields more precise results. Results are displayed in Figure 7 in yellow.²⁰ The within-country business cycle similarity is quite high in most countries, the value of the index being above 0.5 in twelve of them, but it varies a lot among them.

However, we are aware that this index is biased by the number of regions in each country (NR_c). In fact, the correlation between I_c and the number of regions in each country, NR_c , is

¹⁹Although not strictly comparable to our results, as they use less disaggregated datasets and different methodologies, Clark and van Wincoop (2001) confirm the existence of a border effect in some French and German regions. Acedo-Montoya and de Haan (2008), using clustering techniques and a sample 53 NUTS1 regions (12 countries), find that most of the regions belonging to the same country are closely synchronized. However, both of these findings contradict those of Fatas (1997) who suggests that correlation within countries is not very high and has reduced over time for 38 NUTS2 regions (4 countries). Note this sample does not include the common monetary period.

²⁰The results of Luxembourg have been removed from this figure because, being a one-region country, the construction of this index would not make any sense.

-0.57. To correct this effect, we introduce a penalty which depends on the number of regions in each country. We define a new index, $I2_c$, as a linear combination of Ic and NR_c that ranges from 1 to $1/\max(NR_c)$ ²¹ and so $I2_c = \theta Ic + (1 - \theta)NR_c$ where θ is the penalty factor. We use a penalty factor of 0.5. This value gives the same weight to both factors: homogeneity of each cluster and the number of regions within each country. The results of this corrected index are shown in blue in Figure 7, revealing a different picture. Using the corrected index, the UK,²² Italy (IT) and France (FR) appear as the countries with the highest degree of internal synchronization, while Portugal (PT) and the Netherlands (NL) present a high degree of business cycle heterogeneity. All in all, we find heterogeneity in the size of border effects, as expected in H_4 .

4 Concluding remarks

In this paper, we date the business cycles of European regions, for the first time in the literature, and identify clusters among the regions showing similar business cycle behavior. Moreover, we use Finite Mixture Markov models (Frühwirth-Schnatter and Kaufmann, 2008) for the regional analysis. This methodology allows us to overcome some data limitations and technical difficulties that arise in capturing business cycles with heterogeneous data. Additionally, we propose an index to measure within-country homogeneity or border effects. Finally, we employ a more comprehensive dataset than in the previous literature, both in terms of temporal and geographical dimensions.

The main findings of the paper are the following. Comovement among regions is, on average, quite low. However, we find a progressive increase of the spatial correlation during the convergence process towards the creation of the euro area and a sharp rise of comovements among regions during the Great Recession. We identify five groups of European regions with different timings and intensities of their cyclical phases. We also find sizable border effects, i.e., the degree of homogeneity of regional business cycles within countries is quite different.

The similarity of regional business cycles in Europe is an important criterion for implementing common European policies. For instance, common policies might not be equally good for all the regions if there is heterogeneity in business cycle developments across regions. In turn, idiosyncratic features should be addressed taking into account the regional dimension by using either the Cohesion Policy or region-specific national policies.

²¹The highest value, 1, corresponds to the UK with 37 regions and the lowest, $1/37$, to LU.

²²This result coincides with that obtained by Barrios et al. (2003) in which they find a relative homogeneity of cyclical patterns across UK regions. However, they examine just 11 UK regions over the 1966-1997 period and use a different methodology.

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5 Tables

Table 1: Posterior estimates, K=5 and p=2

S_i	$I_{S_i,t} = 1$				$I_{S_i,t} = 0$				num.regions
	$\mu_{S_i}^G$	δ_{1,S_i}^G	δ_{2,S_i}^G	$\xi_{11}^{S_i}$	$\mu_{S_i}^G - \mu_{S_i}^R$	δ_{1,S_i}^R	δ_{2,S_i}^R	$\xi_{00}^{S_i}$	
1	2.15 (0.16)	0.05 (0.08)	0.20 (0.10)	0.70 (0.50 0.89)	-2.60 (0.28)	0.67 (0.32)	-0.08 (0.18)	0.56 (0.31 0.80)	12
2	1.73 (0.20)	-0.13 (0.10)	0.41 (0.10)	0.73 (0.55 0.90)	-2.80 (0.42)	-0.14 (0.30)	0.44 (0.23)	0.55 (0.28 0.81)	13
3	1.26 (0.14)	-0.27 (0.14)	0.16 (0.10)	0.79 (0.62 0.95)	-2.83 (0.24)	-0.45 (0.42)	-0.15 (0.15)	0.57 (0.30 0.87)	15
4	1.07 (0.09)	-0.06 (0.10)	0.05 (0.08)	0.83 (0.68 0.96)	-2.84 (0.21)	0.19 (0.40)	-0.25 (0.10)	0.67 (0.37 0.94)	40
5	0.49 (0.03)	0.16 (0.02)	-0.01 (0.02)	0.86 (0.74 0.97)	-2.70 (0.09)	0.82 (0.05)	-0.37 (0.03)	0.57 (0.24 0.89)	132

Notes: $I_{S_i,t} = 1$ refers to the expansionary cyclical phase, while $I_{S_i,t} = 0$ represents the recessionary period. Standard errors in brackets.

6 Figures

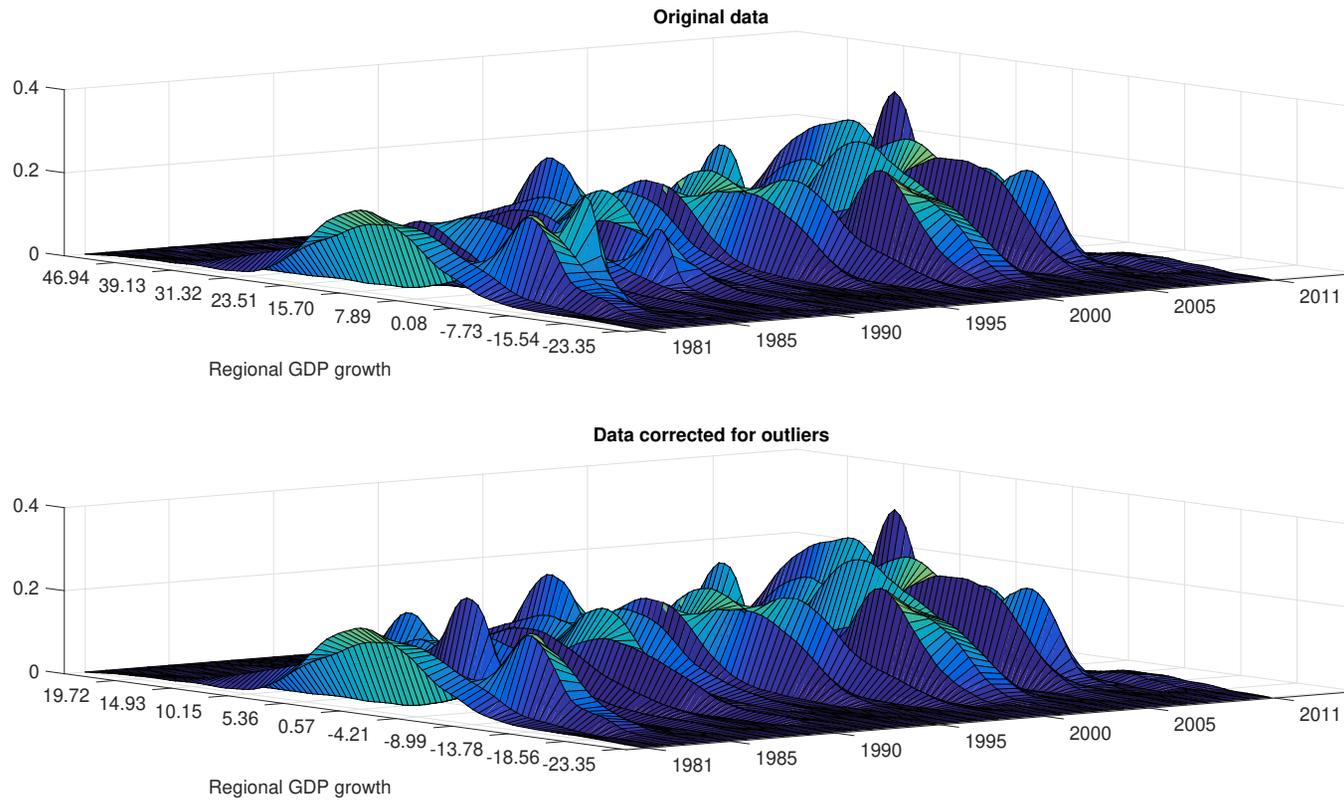


Figure 1: Kernel density over time of regional growth rates

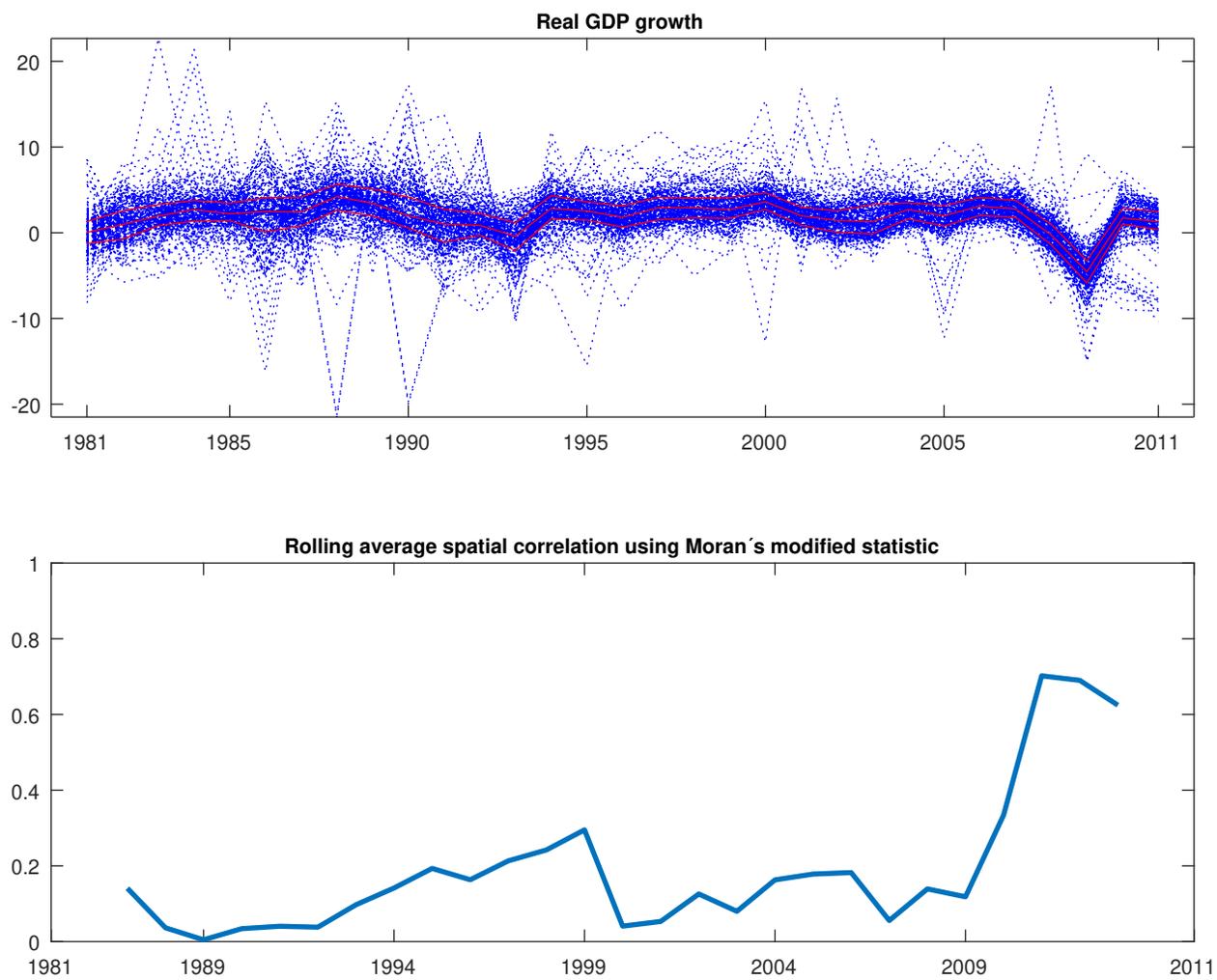


Figure 2: Evolution and comovements between regional growth rates

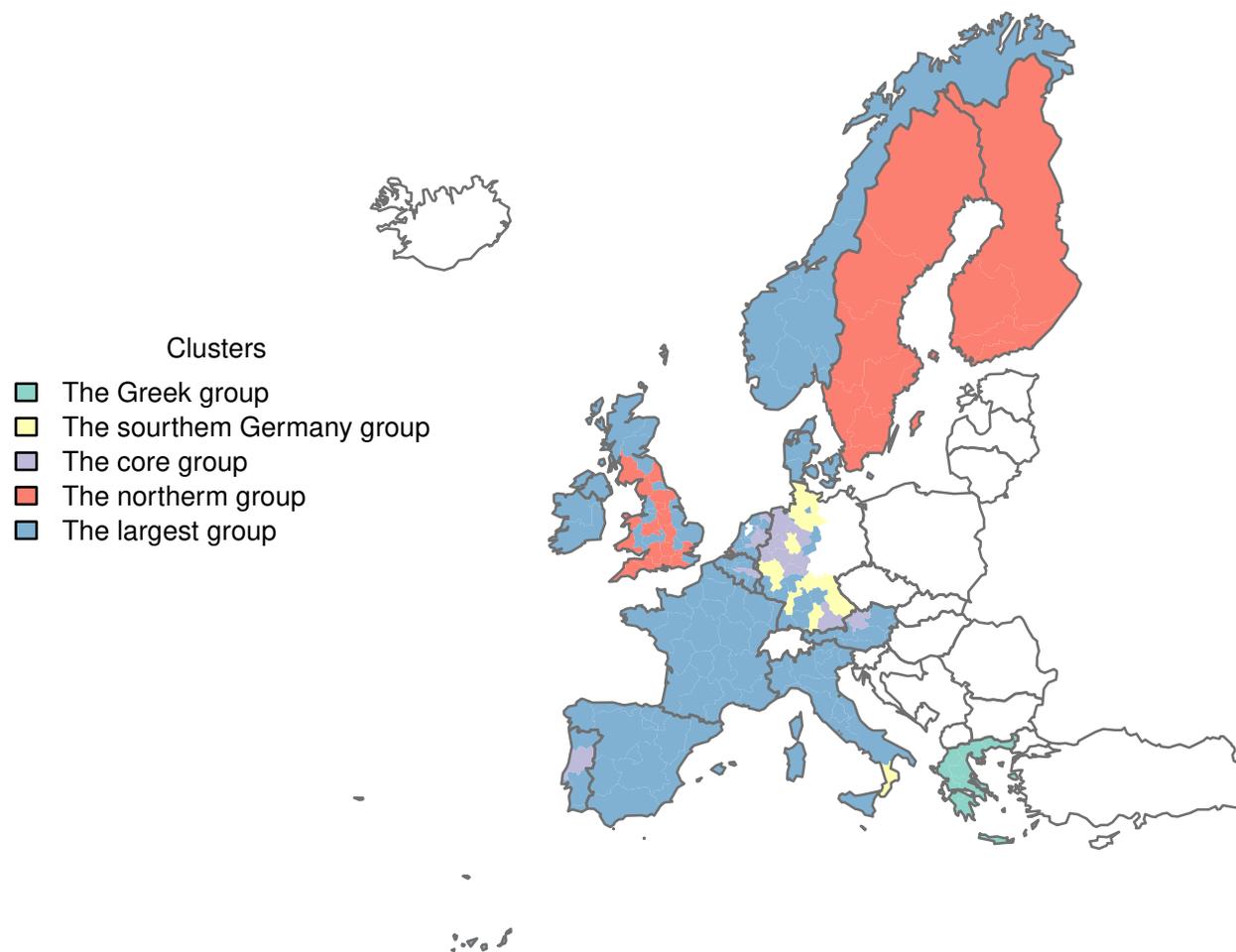


Figure 3: Geographical distribution of regional business cycles into different groups

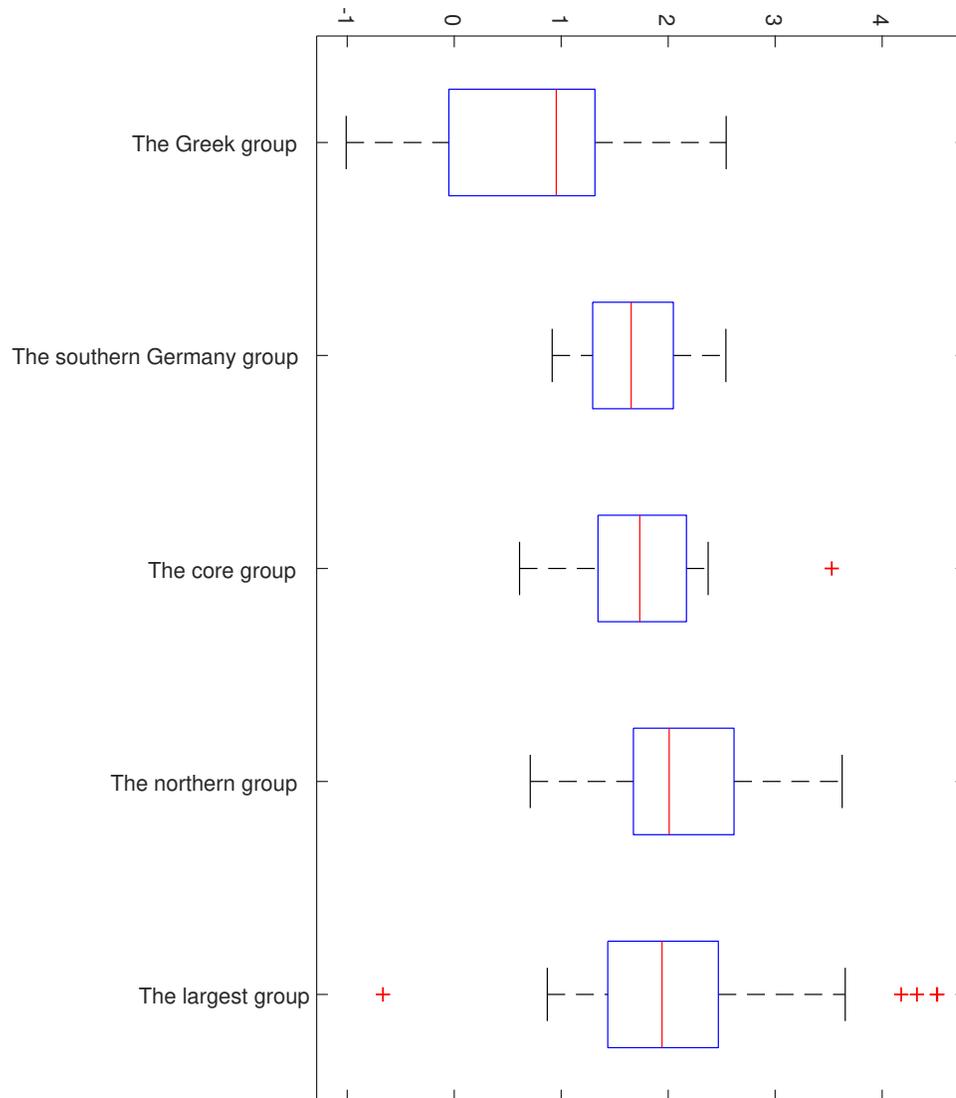


Figure 4: Boxplot of the real GDP growth by group

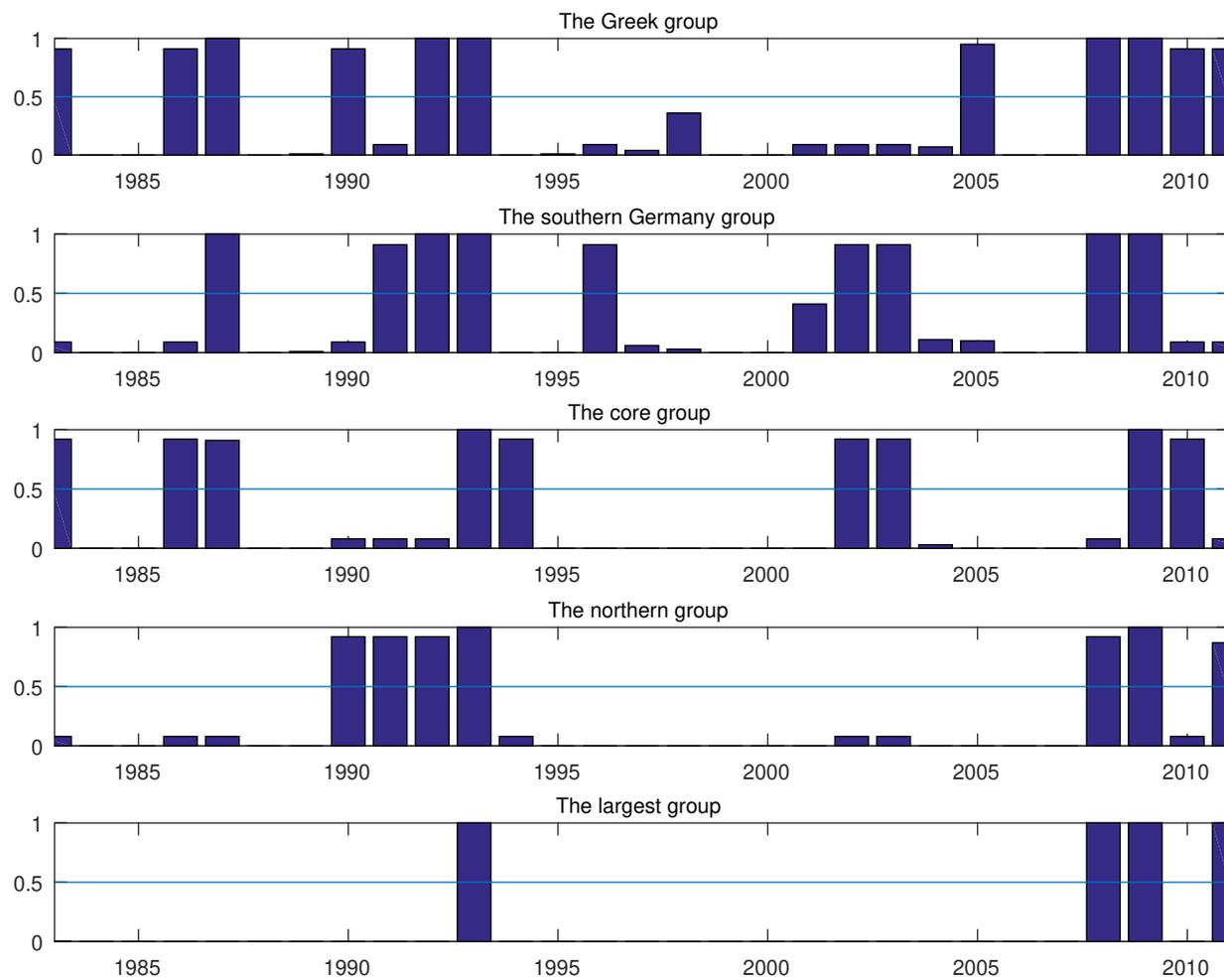


Figure 5: Probability of recession by group $I_t = 0$

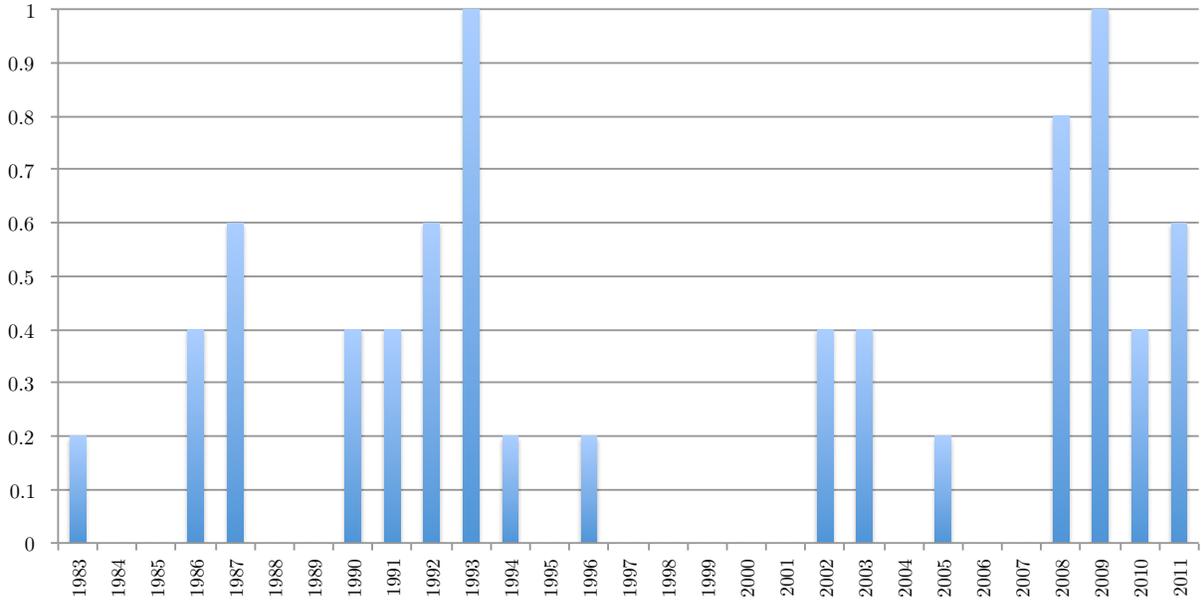


Figure 6: Recession diffusion index

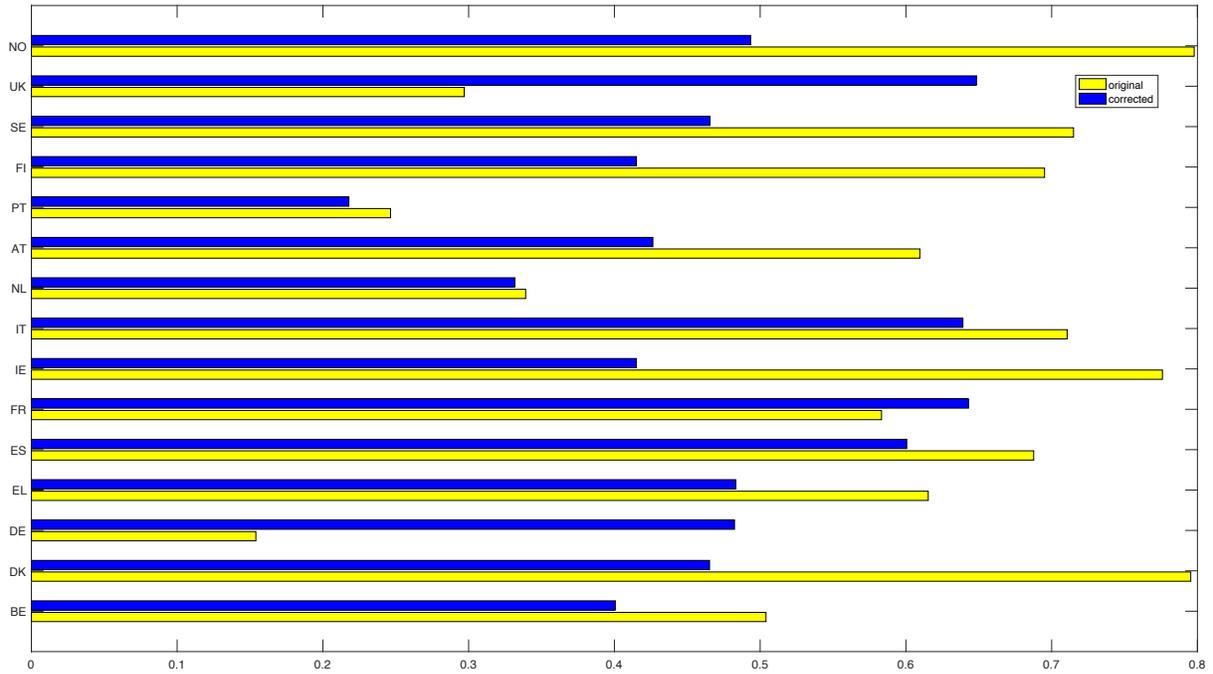
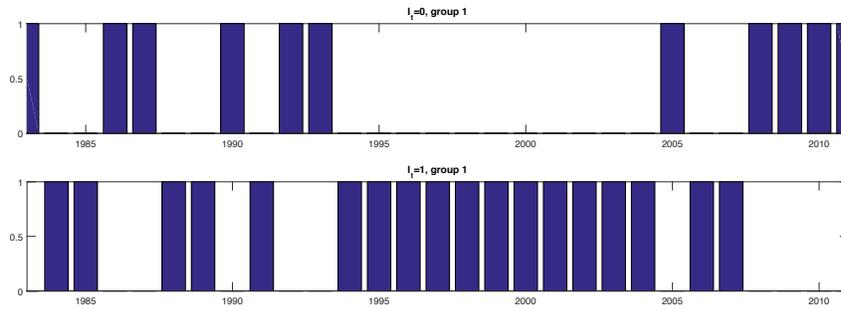
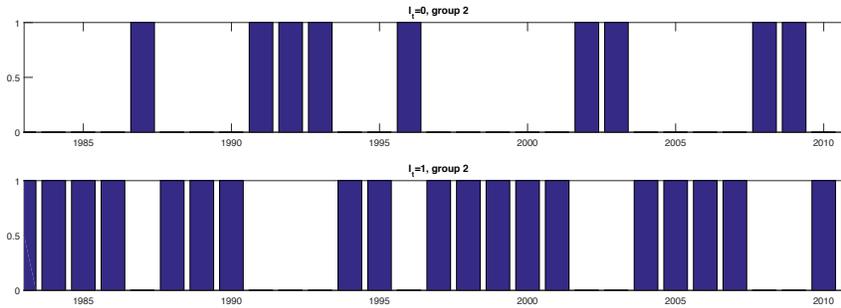


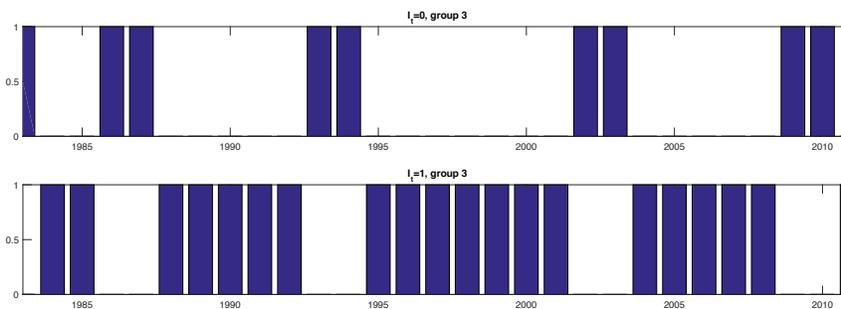
Figure 7: Within-country regional synchronization indexes



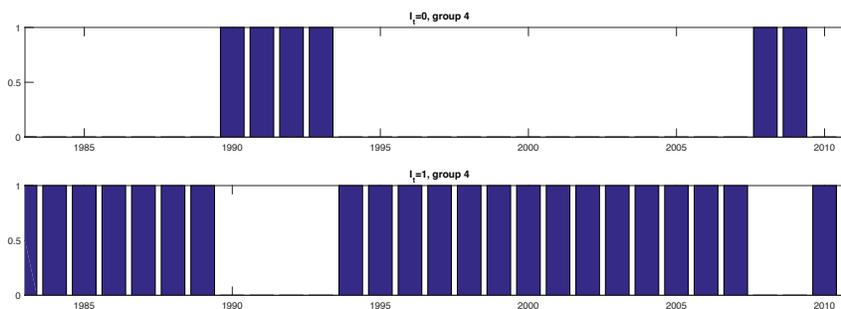
(a) The Greek group



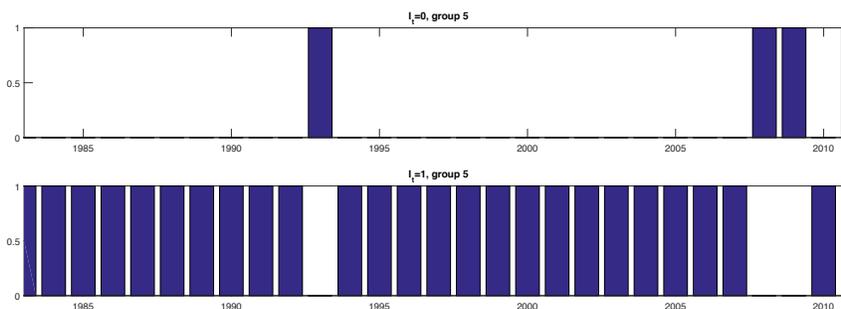
(b) The southern Germany group



(c) The core group



(d) The northern group



(e) The largest group

Figure 8: Business cycles of the different groups

Appendix: Probability by region of being in each group

	G1	G2	G3	G4	G5
BE01 RÉGION DE BRUXELLES-CAPITALE / BRUSSELS HOOFDSTEDELJK GEWEST	0	0	0	0	1
BE21 Prov. Antwerpen	0	0	0.29	0.03	0.68
BE22 Prov. Limburg (B)	0	0	0	0	1
BE23 Prov. Oost-Vlaanderen	0	0	0	0.03	0.97
BE24 Prov. Vlaams-Brabant	0	0	0	0	1
BE25 Prov. West-Vlaanderen	0	0.01	0	0	0.99
BE31 Prov. Brabant Wallon	0	0	0.92	0.08	0
BE32 Prov. Hainaut	0	0	0	0	1
BE33 Prov. Liège	0	0	0.91	0.08	0.01
BE34 Prov. Luxembourg (B)	0	0	0	0	1
BE35 Prov. Namur	0	0	0	0	1
DK01 Hovedstaden	0	0.01	0	0	0.99
DK02 Sjælland	0	0	0	0.01	0.99
DK03 Syddanmark	0	0	0	0	1
DK04 Midtjylland	0	0	0	0	1
DK05 Nordjylland	0	0	0	0.01	0.99
DE11 Stuttgart	0	0	0	0.05	0.95
DE12 Karlsruhe	0.07	0.85	0.01	0	0.07
DE13 Freiburg	0	0.04	0	0.01	0.95
DE14 Tübingen	0	0.01	0	0	0.99
DE21 Oberbayern	0	0	0.92	0.08	0
DE22 Niederbayern	0.09	0.91	0	0	0
DE23 Oberpfalz	0.09	0.91	0	0	0
DE24 Oberfranken	0.09	0.91	0	0	0
DE25 Mittelfranken	0.07	0.42	0	0	0.51
DE26 Unterfranken	0.09	0.91	0	0	0
DE27 Schwaben	0.09	0.91	0	0	0
DE05 BREMEN	0	0	0	0	1
DE06 HAMBURG	0	0.01	0.01	0	0.98
DE71 Darmstadt	0.02	0.04	0.01	0.01	0.92
DE72 Gießen	0	0.02	0.92	0.06	0
DE73 Kassel	0	0	0.92	0.08	0
DE91 Braunschweig	0	0	0.01	0	0.99
DE92 Hannover	0.02	0.28	0.58	0.06	0.06
DE93 Lüneburg	0.09	0.91	0	0	0
DE94 Weser-Ems	0	0	0.92	0.08	0
DEA1 Düsseldorf	0	0	0.66	0.07	0.27
DEA2 Köln	0.09	0.91	0	0	0
DEA3 Münster	0	0.04	0.88	0.08	0
DEA4 Detmold	0.09	0.91	0	0	0
DEA5 Arnsberg	0	0	0.92	0.08	0
DEB1 Koblenz	0.09	0.76	0	0	0.15
DEB2 Trier	0	0	0.03	0.01	0.96
DEB3 Rheinhessen-Pfalz	0	0	0.02	0.01	0.97
DE0C SAARLAND	0	0.02	0.01	0.07	0.9
DE0F SCHLESWIG-HOLSTEIN	0.04	0.72	0.01	0	0.23
EL11 Anatoliki Makedonia, Thraki	0.91	0.09	0	0	0
EL12 Kentriki Makedonia	0.9	0.09	0	0	0.01
EL13 Dytiki Makedonia	0.91	0.09	0	0	0
EL14 Thessalia	0.91	0.09	0	0	0
EL21 Ipeiros	0.91	0.09	0	0	0
EL22 Ionia Nisia	0.89	0.08	0	0	0.03
EL23 Dytiki Ellada	0.91	0.09	0	0	0
EL24 Sterea Ellada	0.91	0.09	0	0	0
EL25 Peloponnisos	0.91	0.09	0	0	0
EL03 ATTIKI	0.62	0.07	0	0	0.31
EL41 Voreio Aigaio	0.91	0.09	0	0	0
EL42 Notio Aigaio	0.35	0.03	0	0.01	0.61
EL43 Kriti	0.91	0.09	0	0	0

	G1	G2	G3	G4	G5
ES11 Galicia	0	0	0	0	1
ES12 Principado de Asturias	0	0	0	0	1
ES13 Cantabria	0	0	0	0.01	0.99
ES21 País Vasco	0	0	0	0	1
ES22 Comunidad Foral de Navarra	0	0	0.01	0.14	0.85
ES23 La Rioja	0	0	0.04	0.02	0.94
ES24 Aragón	0	0	0	0	1
ES03 COMUNIDAD DE MADRID	0	0	0	0	1
ES41 Castilla y León	0	0	0	0.05	0.95
ES42 Castilla-La Mancha	0	0	0	0.01	0.99
ES43 Extremadura	0	0	0.03	0.02	0.95
ES51 Cataluña	0	0	0	0	1
ES52 Comunidad Valenciana	0	0	0	0	1
ES53 Illes Balears	0	0	0	0	1
ES61 Andalucía	0	0	0	0	1
ES62 Región de Murcia	0	0	0.02	0.22	0.76
ES63 Ciudad Autónoma de Ceuta	0	0.01	0.02	0.31	0.66
ES64 Ciudad Autónoma de Melilla	0	0	0.06	0.63	0.31
ES07 CANARIAS	0	0	0	0	1
FR01 ÎLE DE FRANCE	0	0	0	0	1
FR21 Champagne-Ardenne	0.03	0.29	0	0	0.68
FR22 Picardie	0	0	0	0	1
FR23 Haute-Normandie	0	0	0	0	1
FR24 Centre	0	0	0	0	1
FR25 Basse-Normandie	0	0	0	0	1
FR26 Bourgogne	0	0	0	0	1
FR03 NORD - PAS-DE-CALAIS	0	0	0	0	1
FR41 Lorraine	0	0	0	0	1
FR42 Alsace	0	0	0	0	1
FR43 Franche-Comté	0	0.01	0.01	0.03	0.95
FR51 Pays de la Loire	0	0	0	0	1
FR52 Bretagne	0	0	0	0	1
FR53 Poitou-Charentes	0	0	0	0	1
FR61 Aquitaine	0	0	0	0	1
FR62 Midi-Pyrénées	0	0.01	0	0.03	0.96
FR63 Limousin	0	0	0	0	1
FR71 Rhône-Alpes	0	0	0	0	1
FR72 Auvergne	0	0	0	0	1
FR81 Languedoc-Roussillon	0	0.02	0	0	0.98
FR82 Provence-Alpes-Côte d'Azur	0	0.01	0	0	0.99
FR83 Corse	0	0	0	0	1
FR91 Guadeloupe	0	0	0.04	0.55	0.41
FR92 Martinique	0	0	0.07	0.53	0.4
FR93 Guyane	0.01	0	0.05	0.57	0.37
FR94 Réunion	0	0	0.07	0.65	0.28
IE01 Border, Midland and Western	0.04	0.01	0	0	0.95
IE02 Southern and Eastern	0	0.01	0	0	0.99

	G1	G2	G3	G4	G5
ITC1 Piemonte	0	0	0	0.01	0.99
ITC2 Valle d'Aosta/Vallée d'Aoste	0	0	0	0.01	0.99
ITC3 Liguria	0	0	0.02	0	0.98
ITC4 Lombardia	0	0	0	0.02	0.98
ITD1 Provincia Autonoma Bolzano/Bozen	0	0	0.08	0	0.92
ITD2 Provincia Autonoma Trento	0	0	0	0	1
ITD3 Veneto	0	0	0	0	1
ITD4 Friuli-Venezia Giulia	0	0	0	0.01	0.99
ITD5 Emilia-Romagna	0	0	0	0	1
ITE1 Toscana	0	0	0	0	1
ITE2 Umbria	0	0	0	0	1
ITE3 Marche	0	0	0	0.01	0.99
ITE4 Lazio	0	0	0	0	1
IT0F SUD	0	0	0	0	1
ITF2 Molise	0	0	0	0.01	0.99
ITF3 Campania	0	0	0	0	1
ITF4 Puglia	0	0	0	0.01	0.99
ITF5 Basilicata	0	0	0	0.01	0.99
ITF6 Calabria	0.06	0.8	0.14	0	0
ITG1 Sicilia	0	0	0	0	1
ITG2 Sardegna	0	0	0	0	1
LU00 LUXEMBOURG (GRAND-DUCHÉ)	0	0.07	0	0	0.93
NL11 Groningen	0	0	0.92	0.08	0
NL12 Friesland (NL)	0	0	0.26	0.03	0.71
NL13 Drenthe	0	0	0	0	1
NL21 Overijssel	0	0	0.92	0.08	0
NL22 Gelderland	0	0	0.84	0.08	0.08
NL23 Flevoland	0.01	0	0	0.03	0.96
NL31 Utrecht	0	0.08	0	0	0.92
NL32 Noord-Holland	0	0	0	0	1
NL33 Zuid-Holland	0	0	0	0	1
NL34 Zeeland	0	0	0.08	0.86	0.06
NL41 Noord-Brabant	0	0	0	0	1
NL42 Limburg (NL)	0	0	0	0.01	0.99
AT11 Burgenland (A)	0.04	0.01	0	0	0.95
AT12 Niederösterreich	0	0.05	0.25	0.04	0.66
AT13 Wien	0	0	0	0	1
AT21 Kärnten	0	0	0	0	1
AT22 Steiermark	0	0	0	0	1
AT31 Oberösterreich	0	0	0.66	0.05	0.29
AT32 Salzburg	0	0	0	0	1
AT33 Tirol	0	0	0	0	1
AT34 Vorarlberg	0	0	0	0	1
PT11 Norte	0.02	0.12	0	0	0.86
PT15 Algarve	0	0	0	0.01	0.99
PT16 Centro (P)	0	0	0.91	0.08	0.01
PT17 Lisboa	0	0	0	0.01	0.99
PT18 Alentejo	0	0.01	0.29	0.26	0.44
PT02 Região Autónoma dos AÇORES	0.03	0.19	0	0.02	0.76
PT03 Região Autónoma da MADEIRA	0.09	0.79	0	0.01	0.11
FI13 Itä-Suomi	0	0	0.07	0.85	0.08
FI18 Etelä-Suomi	0	0	0.08	0.92	0
FI19 Länsi-Suomi	0	0	0.08	0.92	0
FI1A Pohjois-Suomi	0	0	0.08	0.89	0.03
FI02 ÅLAND	0.01	0	0.05	0.73	0.21

	G1	G2	G3	G4	G5
SE11 Stockholm	0	0	0.08	0.91	0.01
SE12 Östra Mellansverige	0	0	0.07	0.92	0.01
SE21 Småland med öarna	0	0	0.08	0.9	0.02
SE22 Sydsverige	0	0	0.08	0.92	0
SE23 Västsverige	0	0	0.08	0.92	0
SE31 Norra Mellansverige	0	0	0.08	0.89	0.03
SE32 Mellersta Norrland	0	0.01	0.08	0.91	0
SE33 Övre Norrland	0	0.04	0.05	0.78	0.13
UKC1 Tees Valley and Durham	0	0	0.08	0.41	0.51
UKC2 Northumberland and Tyne and Wear	0	0	0.07	0.73	0.2
UKD1 Cumbria	0	0	0.08	0.92	0
UKD2 Cheshire	0	0	0	0	1
UKD3 Greater Manchester	0	0	0	0	1
UKD4 Lancashire	0	0	0.01	0.18	0.81
UKD5 Merseyside	0	0	0	0	1
UKE1 East Yorkshire and Northern Lincolnshire	0	0	0.04	0.44	0.52
UKE2 North Yorkshire	0	0	0.04	0.65	0.31
UKE3 South Yorkshire	0	0	0.06	0.71	0.23
UKE4 West Yorkshire	0	0	0.05	0.59	0.36
UKF1 Derbyshire and Nottinghamshire	0	0.01	0.08	0.85	0.06
UKF2 Leicestershire, Rutland and Northamptonshire	0	0	0.08	0.82	0.1
UKF3 Lincolnshire	0	0	0.03	0.37	0.6
UKG1 Herefordshire, Worcestershire and Warwickshire	0	0	0.03	0.39	0.58
UKG2 Shropshire and Staffordshire	0	0	0.06	0.56	0.38
UKG3 West Midlands	0	0	0.08	0.61	0.31
UKH1 East Anglia	0	0	0.04	0.39	0.57
UKH2 Bedfordshire and Hertfordshire	0	0	0	0.2	0.8
UKH3 Essex	0	0	0.08	0.92	0
UKI1 Inner London	0	0	0.08	0.84	0.08
UKI2 Outer London	0	0	0.05	0.59	0.36
UKJ1 Berkshire, Buckinghamshire and Oxfordshire	0	0	0.08	0.91	0.01
UKJ2 Surrey, East and West Sussex	0	0	0.08	0.85	0.07
UKJ3 Hampshire and Isle of Wight	0	0	0.08	0.88	0.04
UKJ4 Kent	0	0	0.03	0.34	0.63
UKK1 Gloucestershire, Wiltshire and Bristol/Bath area	0	0	0.06	0.9	0.04
UKK2 Dorset and Somerset	0	0	0.08	0.84	0.08
UKK3 Cornwall and Isles of Scilly	0	0	0.07	0.71	0.22
UKK4 Devon	0	0	0.08	0.91	0.01
UKL1 West Wales and The Valleys	0	0	0.06	0.58	0.36
UKL2 East Wales	0	0	0	0	1
UKM2 Eastern Scotland	0	0	0.01	0.18	0.81
UKM3 South Western Scotland	0	0	0.05	0.72	0.23
UKM5 North Eastern Scotland	0	0	0.01	0	0.99
UKM6 Highlands and Islands	0	0	0	0.07	0.93
UKN Northern Ireland	0	0	0	0	1
NO01 Oslo og Akershus	0	0	0	0.02	0.98
NO02 Hedmark og Oppland	0	0	0	0	1
NO03 Sør-Østlandet	0	0	0	0	1
NO04 Agder og Rogaland	0	0	0	0	1
NO05 Vestlandet	0	0	0	0	1
NO06 Trøndelag	0	0	0	0	1
NO07 Nord-Norge	0	0	0	0	1