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Markus Ahlborn , Marcus Wortmann


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# The core–periphery pattern of European business cycles: A fuzzy clustering approach

**Markus Ahlborn (Corresponding Author)**
Georg-August-University Göttingen
Platz der Göttinger Sieben 3
37073 Göttingen, Germany
E-mail: markus.ahlborn@wiwi.uni-goettingen.de

**Marcus Wortmann**
Georg-August-University Göttingen
Platz der Göttinger Sieben 3
37073 Göttingen, Germany
E-mail: marcus.wortmann@wiwi.uni-goettingen.de

## Abstract

The literature on business cycle synchronization in Europe frequently presumes an alleged 'core–periphery' pattern without providing empirical verification of the underlying cyclical (dis)similarities or the supposed but unobservable 'European business cycle(s).' To provide a data-based country group analysis, we apply a fuzzy clustering approach to quarterly output gap series of 27 European countries over the period 1996–2015. Our results confirm the existence of a persistent core cluster as opposed to clusters on the Eastern and Southern European peripheries, highlighting the inadequate composition of the euro area (EA). Moreover, we find that Germany's business cycle is not a suitable substitute for the core. By analyzing the relation between the identified 'European core business cycle' and the peripheral cycles over time, we show diverging patterns for the southern periphery after the financial crisis as well as convergence for the eastern periphery.

**JEL classification**: C38, E32, F15, F45
**Keywords**: business cycles, core–periphery, euro area, fuzzy cluster analysis

# 1. Introduction

Since the adoption of a single European currency in the early 1990s, the synchronization of business cycles between European economies has become a major field of both theoretical and empirical research. The main objective of this literature is to investigate the extent to which a common 'European business cycle' is established that applies as a basic condition for a smoothly working monetary union (Artis et al. 2004). In fact, the global financial crisis and the subsequent euro crisis have rather provided evidence of large economic discrepancies primarily between groups of countries within and beyond the euro area (EA). Therefore, cyclical (dis)similarities should be considered from a group perspective, for instance between the 'vulnerable' economies in Southern Europe (European Commission 2014) or the Central and Eastern European countries (CEECs; Fidrmuc and Korhonen 2006; Stanisic 2013; Di Giorgio 2016) and the Central European countries.

A conventional scheme for the analysis of business cycle patterns among groups of (prospective) EA members is the core–periphery division (Camacho et al. 2006). As opposed to the Southern, the Eastern and sometimes the Northern European 'periphery,' a homogeneous 'core' group is typically identified among the founding EU Member States, with Germany at its center (see, for instance, Arestis and Phelps 2016). Assuming that the supposed core countries share similar business cycles, say the 'European core business cycle,' policy makers may thus be interested in how closely countries are associated with this cycle compared with other group-specific European cycles. However, the identification of core and peripheral European business cycles and the potential group composition remain inconsistent in the literature. In this paper we propose a more comprehensive way to explore the core–periphery pattern empirically by conducting a fuzzy cluster analysis of business cycle time series, which allows us to provide detailed information on countries' accordance with group-specific European business cycles.

Some previous studies, like those by Artis and Zhang (2002), König and Ohr (2013) and Wortmann and Stahl (2016), identify a suitable core group for the EA through cluster analyses based on different sets of static macroeconomic criteria, partly related to the optimum currency area (OCA) theory. Among these cyclical similarities are only considered implicitly. Despite taking into account a variety of criteria, the multivariate approaches face difficulties in selecting and weighting the potential variables that may be regarded as relevant preconditions for a smoothly working monetary union. Consequently the obtained country groups may be driven by inadequate, potentially correlated country features dominating the clustering process. Artis and Zhang (2001) also point to the fact that multivariate cluster analysis groups countries regardless of whether their similarity is due to negative or positive features in terms of a well-functioning monetary union. If the driving factors of the group assignment remain unclear, the suitability of any cluster for monetary unification will be unclear too. However, the few multivariate analyses are the exceptions, as the vast majority of studies dealing with the core–periphery division concentrate on business cycle synchronization.[1] For these reasons the present paper focuses on business cycles and connects all the results to the extensive literature summarized below.

When time series data on business cycles are used, basically two different ways of assessing the core–periphery pattern can be distinguished. Darvas and Szapary (2008), Hughes Hallet and Richter (2008), Crespo-Cuaresma and Fernández-Amador (2013), Lehwald (2013), Caporale et al. (2015), Arestis and Phelps (2016) and Belke et al. (2016) analyze business cycles using various methods within or across putative groups like the ‘GIPS countries,’ the ‘peripheral countries’ or the ‘core countries’ that are set in advance. Hence, the assignment of each country to its group is subject to general assumptions at best taken from the literature. As pointed out by Belke et al. (2016), ‘there exists no exact definition as to which countries belong to the core or to the periphery.’ For instance, there is no consensus on the classification of Italy. Some studies locate it on the southern periphery (e.g. Hughes Hallet and Richter 2008; Caporale et al. 2015), but recent evidence suggests that it shows a great deal of business cycle synchronization with the core (Belke et al. 2016;

[1] In the OCA theory, business cycle synchronization is regarded as a ‘catch all’ or ‘meta criterion’ in analyzing the costs and benefits of monetary unions. Participating countries with synchronized business cycles will need less autonomy in monetary and exchange rate policies, and thus the costs of losing direct control over such policy areas are reduced (Mongelli 2005). However, whether having synchronized business cycles should be considered as a prerequisite for a smoothly working monetary union is still subject to debate. According to the endogeneity hypothesis of Frankel and Rose (1997), a high degree of business cycle synchronization may rather be achieved ex post due to increased trade linkages. De Haan et al. (2008) and Kappler and Sachs (2013) provide surveys of business cycle synchronization in Europe.

Campos and Macchiarelli 2016). Following the idea that countries will be more or less connected to any existing group-specific European business cycle, the fuzzy clustering approach adopted here allows us to quantify each country's degree of belongingness to all the identified clusters. Moreover, while the literature focuses on the distinction between the core and the Southern European periphery, the classification of the CEECs, among them prospective EA member countries, is of special interest.

The second approach to classifying countries as belonging to the 'core' or the 'periphery' is to analyze their relation to a reference cycle. The first authors to do so are Bayoumi and Eichengreen (1993), who base their analysis on correlations of the national supply and demand shocks with those of Germany as an 'anchor' or 'center' country. Pentecôte and Huchet-Bourdon (2012) repeat this exercise but additionally control for correlations vis-à-vis the EA (11) reference area. They find that 'France, rather than Germany has served as an anchor point for convergence of the other EU countries.' The study by Aguiar-Conraria et al. (2013) uses wavelet tools to analyze the synchronization between an aggregate EA (10) economic sentiment cycle and the national cycles. Their findings also reveal that the composition of a core group is not quite intuitive, because the core itself can even be divided into a 'German pole' and a 'French pole' also comprising Italy and Spain, respectively. Based on industrial production data, Aguiar-Conraria and Soares

(2011) reach similar conclusions, confirming the leading role of the French business cycle.

Obviously, an important assumption of such analyses is the choice of a suitable proxy for the supposed but unobservable European business cycle. So far Germany's business cycle, a weighted EA average and the EA's aggregate cycle are used frequently as such reference measures for business cycle synchronization analyses.[2] Using a representative core country, like Germany, as a reference is generally justified by the 'leading economy' argument but will be problematic if this country's business cycle, temporarily and for idiosyncratic reasons, deviates from all the others. As will be discussed in Section 3 below, our results indicate that Germany's cycle indeed does not qualify as a suitable anchor. Even the EA's aggregate cycle is an inappropriate proxy for the European core business cycle, as it may be distorted by large economies, like Spain or Italy, that possibly belong to peripheral clusters. Darvas and Szapary (2008) cope with this problem to a certain extent by estimating a common factor of the supposed core group as a reference. However, membership of this core is again arbitrary and not based on cyclical similarities. Finally, Camacho et al. (2006) and Mink et al. (2012) state that neither the existence of one single European cycle nor its compliance with any chosen reference can readily be assumed in advance, casting doubt on many results of previous business cycle analyses.

[2] See, for instance, Artis and Zhang (1997), Furceri and Karras (2008), Afonso and Sequeira (2010), Savva et al. (2010), Aguiar-Conraria and Soares (2011), Gächter et al. (2012), Mink et al. (2012) and Kolasa (2013), among others.

Similarly, the previous clustering analyses of Artis and Zhang (2002), Boreiko (2003), Kozluk (2005), Crowley (2008) and Quah (2014) assess the suitability of (prospective) EA member countries by grouping them according to their synchronicities with the same references. The clustering algorithms used are based on static feature data, such as the pairwise correlation coefficients between the national and the reference cycle. However, as pointed out by Mink et al. (2012), the simple correlation coefficient of two time series does not provide a proper basis for assessing the coherence of the business cycles. Despite perfectly coinciding phases of up- and downswings, the cycles may only be correlated imperfectly due to their heteroscedasticity. Conversely, in the case of perfect correlation, the amplitude of the cycles may still differ substantially. To deal with these shortcomings, we apply a time series cluster analysis that is based on cyclical distances. Instead of imposing any reference cycle beforehand, the algorithm generates group-specific representative cycles during the clustering process. Hence, we let the data decide the number, location and shape of any such reference cycle, be it that of a European core or any other peripheral cluster. This enables us to investigate further whether there is convergence or divergence between the peripheral cycles and the European core cycle, especially since the global financial crisis and the subsequent euro crisis. While the previous cluster analyses do not include the recent time period, we specifically focus on the impact of these crises on the cluster structure. Some evidence by Gächter et al. (2012) and Degiannakis et al. (2014) indeed shows that the countries that were most affected by the crises, mainly on the southern EA periphery, experienced a decline in synchronization with the EA aggregate cycle thereafter. Ferroni and Klaus (2015) also find that, since the outbreak of the crisis, the Spanish cycle fluctuations have evolved asymmetrically to the other EA (core) countries of their study (Germany, France and Italy). We contribute to this rather limited literature by studying the changes that the crises caused for the core–periphery pattern of 27 European countries, including the CEECs. Therefore, we divide our sample into a 'pre-crisis period' from 1996 to 2007 and a 'post-crisis period' from 2008 to 2015.

In a nutshell, this paper's purpose is to clarify empirically both the number of existing European business cycles and the countries belonging to them. In particular, the following questions will be answered. (1) Is there a European core business cycle? (2) How many peripheral cycles have been established and how do they relate to the core cycle? (3) To what extent can each country's business cycle be associated with these different business cycle clusters?

We address these questions simultaneously by employing a fuzzy clustering approach to output gaps extracted from national real GDP time series. The fuzzy c-means (FCM) algorithm directly separates the most similar business cycles into several clusters, assigning to each country a degree of membership of the group-specific European business cycles at the center of the clusters. To our best knowledge, this immediate way of assessing groups in the data has not yet been applied to output gap series and provides some advantages for both future research and policy advice. In particular, our contributions to the literature are the following. First, we offer a precise classification of countries within the complex core–periphery pattern of European business cycles, clarifying the position of controversial cases like Italy, the CEECs and Germany as an anchor country. This classification can provide valuable guidance for future studies on business cycle synchronization, in which core and peripheral country groups have to be set beforehand. Second, we specifically analyze how this core–periphery pattern has changed over time, especially since the global financial crisis. Third, we provide a European core business cycle that can be used as a more suitable anchor cycle in future studies. Finally, fourth, the relative belongingness of each country to this representative core cycle provides information on the costs of sharing a common currency with the core countries in terms of business cycle synchronization.

With regard to the three questions posed above, our main results can be summarized as follows. (1) We find evidence supporting the existence of a persistent core cluster among the Central European economies. Remarkably, Germany exhibits a lower degree of belongingness to the European core cycle, which clearly questions its common use as a reference country. (2) There are some peripheral business cycle clusters corresponding to regional proximity in Europe: the CEECs split up into clusters on the eastern periphery, most evidently in the Baltic and the South Eastern region. These clusters have apparently converged towards the core since the global financial crisis of 2008/2009, contrary to the members of the southern periphery, the other distinct business cycle cluster to be found in the data. This latter cluster has rather diverged from the core since the crisis. (3) Among other findings the 'core membership coefficients' show that especially the 'EA outs' and 'EU outs,' Denmark, Sweden, Switzerland and the UK, as well as some CEECs, especially Hungary and to a lesser degree the Czech Republic and Poland, could adopt the euro at lower costs than countries on the eastern and southern peripheries, as they apparently possess greater business cycle similarities to the core group.

The remainder of this paper is organized as follows. Section 2 introduces the data set and the clustering methodology that we employ. Section 3 presents the results of the main cluster analyses, including the sample splits, and studies the relationship between the European core business cycle and the peripheral cycles. Moreover, the robustness of our findings is checked by altering the clustering design and the distance measurement as well as by dropping the crisis years 2008/2009 and including other OECD control countries. Finally, section 4 concludes.

# 2. Methodology

### 2.1. Data and filtering

The following cluster analyses are based on output gaps extracted from time series of (seasonally adjusted) quarterly real GDP for 25 EU Member States (the EU-28 minus Cyprus, Malta and Luxembourg) plus Norway and Switzerland ranging from 1996 Q1 to 2015 Q4. We consider the latter two countries as they are highly integrated with the EU and because we try to give a comprehensive picture of European business cycles regardless of EU or EA membership. However, the cluster solutions obtained are not sensitive to their inclusion. The time series for most of the countries are collected from the OECD main economic indicators (Belgium, Denmark, Germany, Greece, Spain, France, Italy, the Netherlands, Austria, Portugal, Finland, Sweden, the United Kingdom, Norway, Switzerland, Ireland, Bulgaria, Romania, Hungary, the Czech Republic, Croatia, Poland and Slovakia, plus – for robustness purposes – the USA, Japan and Korea). The remaining statistics, for Estonia, Latvia, Lithuania and Slovenia, are obtained from the Oxford Economics database. The reason for not considering previous business cycle data is the lack of reasonable data for the CEECs, of which the cyclical accordance with the core countries may be regarded as a key criterion for future accession to the monetary union.

To avoid dropping any further data points at the edges of the sample period, we extract the stationary cyclical components from the time series using the band-pass filter developed by Christiano and Fitzgerald (2003, [CF]). The filter is set to extract periodic fluctuations lasting between 6 and 32 quarters.

For robustness purposes, however, we also apply the high-pass filter by Hodrick and Prescott (1997, [HP]), which does not change the general cluster solutions apart from some deviations in membership degrees (see Section 3.4). All the output gaps are then expressed as a percentage of the cyclical component of the trend component. We choose the CF band-pass and the HP high-pass filter as these are two of the most commonly used filters in the literature with which to compare our results. The CF filter is used for the main analysis, as it is specifically suitable for GDP series supposing a random walk with drift. It dominates the other commonly used Baxter–King band-pass filter in real-time applications and does not require the omission of data points at the beginning or end of the time series (Christiano and Fitzgerald 2003).

### 2.2. Fuzzy c-means clustering

The FCM algorithm that we employ is a widely used unsupervised clustering technique generalized by Bezdek (1981).[3] Its purpose is to partition the data into a given number of *c* clusters, each characterized by a cluster 'centroid' or 'prototype' at the center. An iterative procedure varies the location of these centroids to find the solution, which minimizes the weighted sum of the squared Euclidean distances[4] between the objects (here countries) and the

[3] The following description of FCM is based on Wang and Zhang (2007). Liao (2005) provides a short history of this method in his survey of time series clustering. For further details see Kaufman and Rousseeuw (2005).

[4] The FCM algorithm was developed using the Euclidean distance norm (l1 norm), which we use for our main analyses. For robustness purposes, in section 3.4 we also perform the clustering with the 'Manhattan' distance norm (l2 norm). Having time series data of equal length and scale, we rely on these two commonly used standard distance measures as they are

centroids. During that process each object is repeatedly given a set of weights corresponding to the similarity that it exhibits to the varying centroids. The more closely an object resembles the centroid of a specific cluster, the greater is the weight that it receives for that cluster. By using these weights, also called membership coefficients, the coordinates of the centroids are recalculated as similarity-weighted averages ('c-means') of all the objects until an optimal solution is found. As the membership coefficients sum up to one, the fuzzy partition matrix $u$ indicates how close an object is to the centroid of one cluster relative to the others.

In particular, the following objective function should be minimized:

$$J_m(U,V) = \sum_{i=1}^{n}\sum_{j=1}^{c} u_{ij}^{m} \left\|x_i - v_j\right\|^2 \qquad (1)$$

where $u$ is the fuzzy membership matrix indicating the weights of time series $x_i$ in each cluster j and $\left\|x_i - v_j\right\|^2$ denotes the squared Euclidean distance between the time series $x_i$ and each cluster's centroid time series $v_j$, while m stands for the fuzzifier.[5] Minimizing J under the constraints $0 < \sum_{i=1}^{n} u_{ij} < n$ , $\sum_{j=1}^{c} u_{ij} = 1$ and $\sum_{j=1}^{c}\sum_{i=1}^{n} u_{ij} = n$ yields:

parameter-free and competitive with other, more complex approaches that have been developed for time series clustering (Wang et al. 2012).

[5] The fuzzifier controls the degree of fuzziness during the clustering process. According to Nikhil and Bezdek (1995), m is usually set between 1.5 and 2.5 depending on the degree of 'fuzziness' or 'overlap' in the data. Depending on the length of the time series we investigate and hence depending on the degree of fuzzy overlap in our different analyses, we adjust m to values within the usual bounds to achieve the highest silhouette (explained below) at a reasonable level of fuzziness.

$$v_j = \frac{\sum_{i=1}^{n}(u_{ij})^m x_i}{\sum_{i=1}^{n}(u_{ij})^m} \quad , \ 1 \le j \le c \tag{2}$$

$$u_{ij} = \left[\sum_{g=1}^{c}\left(\frac{\|x_i - v_j\|^2}{\|x_i - v_g\|^2}\right)^{1/(m-1)}\right]^{-1}, \ 1 \le j \le c, \ 1 \le i \le n \tag{3}$$

The algorithm generally proceeds in the following way:

1. Randomly initialize $u_{ji}$
2. Calculate *c* cluster centroids $v_j$ with equation (2)
3. Update *u* according to equation (3)
4. Calculate objective function J
5. Return to step 2 until the improvement in J is less than the selected threshold

In the context of business cycle analysis, the resulting centroid time series $v_j$ correspond to the existing group-specific European business cycles, whereas the respective membership coefficient matrix *u* provides detailed information on the extent to which a country can be assigned to each of the identified centroid cycles. Since a higher membership coefficient signifies greater proximity to the respective cluster's centroid, this allows a ranking of countries according to their degree of belongingness.

A wide array of different clustering algorithms is available. However, we are convinced that the FCM algorithm best suits our research purposes, as its properties – clustering that is fuzzy and partitional – offer several advantages over other algorithms for our application. First, as mentioned above, fuzzy clustering – as opposed to 'crisp' or 'hard' clustering algorithms (e.g. those applied by Camacho et al. 2006 and 2008) – allows for different degrees of membership of all the clusters and does not assign countries irrevocably and exclusively to just one group. On the one hand, such fuzziness enables us to rank the countries according to their cyclical similarities to the European core business cycle, providing information on the costs of joining the monetary union with the core countries. On the other hand, a fuzzy algorithm is better suited to dealing with outliers. In a crisp partition, outliers tend to form separate clusters containing only that single object, while, in a fuzzy partition, they tend to lie between the clusters exhibiting equal membership coefficients. Consequently, the fuzzy partition is less dominated by such single-object clusters, so outliers can be detected without distorting the remaining group structure (Bezdek et al. 1982).

Choosing a partitional algorithm as opposed to one that is 'hierarchical'[6] (e.g. that employed by Camacho et al. 2006) offers a further advantage for our purposes. While the FCM algorithm does not provide information on the cluster hierarchy, it identifies cluster centroids as similarity-weighted averages

[6] Most hierarchical clustering algorithms merge objects and clusters in an agglomerative order, that is, initially all the objects form single clusters and are subsequently merged until there is one cluster comprising all the objects. These mergers are informed by distance measures (objects and/or clusters with the smallest distance are merged) and the grouping process can be depicted in a dendrogram.

of all the countries based on their membership coefficients.[7] Using these representative cycles, we investigate their relationship over time, which clearly sets our analysis apart from previous cluster analyses on business cycle data that only focus on the classification of countries.

However, the results of such a partitional cluster analysis will depend on the supposed number of clusters, which we do not know beforehand. The problem of finding an optimal $c$ without any prior information is known as cluster validity and requires some measurement to compare the quality of the achieved cluster solutions with changing numbers of clusters.[8] According to Nikhil and Bezdek (1995), the number of clusters to choose is generally between two and the square root of n. Note that increasing the number of clusters and hence creating more centroids will most likely alter individual membership coefficients, as these are relative values. With just 27 countries in our sample, the illustration of all the cluster solutions thus allows us to trace the changes in the cluster assignment. Following Artis and Zhang (2002), we consider the average silhouette value $s(i)$ for the comparison of these cluster solutions, which is defined as:

$$s(i) = \frac{b(i) - a(i)}{\max[a(i), b(i)]} \tag{4}$$

$a_i$: $average\ distance\ from\ the\ ith\ point\ to\ the\ other\ points\ in\ the\ same\ cluster\ as\ i$

[7] This ‘weighting by similarity’ constitutes a major advantage over ‘crisp’ partitional algorithms, such as k-means, as well. The centroids of k-means clustering are simply the averages of all the members of the clusters, while the centroids calculated with FCM are more influenced by countries close to the center of a particular cluster, as indicated by the membership coefficients.

[8] For a survey on this issue, see Wang and Zhang (2007).

$$b_i: minimum\ average\ distance\ from\ the\ ith\ point\ to\ points\ in\ different\ clusters$$

The silhouette measures how well a cluster solution matches the actual data. Its values range from -1 to +1, with higher values indicating a superior solution, that is, the objects are well matched within their own cluster and poorly matched by the others. Hence, a higher sample average value for $s(i)$ indicates a cluster solution fulfilling the objectives of a cluster analysis – homogeneity within and heterogeneity between clusters – to a higher degree.

## 3. Results

### 3.1. Business cycle clusters in Europe, 1996–2015

The results of our main cluster analysis are presented in Table 1, which summarizes the membership coefficients of different numbers of clusters $c$ for all 27 countries. A membership coefficient close to 1 indicates that the country is close to the center of its cluster, while low values indicate a large distance between the country and the respective cluster centroids. The classification of countries according to their highest membership coefficient (bold figures) shows a clear core–periphery pattern of European business cycles. Every specification yields a cluster, which is centered by those countries typically referred to as the European core countries.

This core cluster consists of the following twelve countries ranked by their average membership coefficients over all the cluster solutions: Austria (0.97), France (0.9–0.99), Denmark (0.92–0.96), Italy (0.88–0.98), the Netherlands (0.86–0.97), the UK (0.8–0.96), Hungary (0.77–0.94), Sweden (0.78–0.9), Switzerland (0.72–0.93), Germany (0.76–0.84), Belgium (0.61–0.97) and Finland (0.60–0.76). Quite surprisingly, Germany's membership coefficients are even slightly lower than those of Hungary, Sweden and the UK, all countries that are not part of the EA. This confirms previous evidence questioning the 'leading role' of the German business cycle (e.g. Aguiar-Conraria and Soares 2011; Pentecôte and Huchet-Bourdon 2012; Aguiar-Conraria et al. 2013) and is a strong indication against using Germany's cycle as a proxy for the European core business cycle (as for example in the analyses by Artis and Zhang 2002, Boreiko 2003 and Campos and Macchiarelli 2016). Belgium, another country that might be expected to be near the center of the core, is not a clear member of this cluster either. The membership coefficients show that it lies between the core (0.61) and the southern periphery (0.37) at $c$=5. At first sight the clear core membership of Italy and Hungary might seem surprising, given that they are sometimes assigned to peripheral clusters (especially Italy) or not included in an analysis of the European core–periphery pattern at all (especially Hungary). As described above, there is some controversy over the classification of Italy in the literature. We find evidence that Italy should not be included in a peripheral country group, as performed for example by Hughes-Hallet and Richter (2008), Caporale et al. (2015) and Belke et al. (2016). We also confirm the consensual finding of the literature on the synchronization of the CEECs that Hungary is the country that is the most synchronized with the EA (see Fidrmuc and Korhonen 2006; Savva et al. 2010; Kolasa 2013; Di Giorgio 2016). The synchronization with the core is so far advanced that it should be assigned to a core group rather than a group of CEECs, as in the study by Arestis and Phelps (2016).

**Table 1: FCM Results (Whole Period 1996 Q1–2015 Q4)**

| | 3-Cluster Solution | | | 4-Cluster Solution | | | | 5-Cluster Solution | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| ***m=1.5 CF Filtered Data*** | ***Cluster 1 Core*** | *Cluster 2 Baltics* | *Cluster 3 Eastern P.* | ***Cluster 1 Core*** | *Cluster 2 Baltics* | *Cluster 3 Eastern P.* | *Cluster 4 Southern P.* | ***Cluster 1 Core*** | *Cluster 2 Baltics* | *Cluster 3 Eastern P.* | *Cluster 4 Southern P.* | *Cluster 5 Bul. & Rom.* |
| Austria | **0.97** | 0.00 | 0.03 | **0.97** | 0.00 | 0.01 | 0.02 | **0.97** | 0.00 | 0.01 | 0.02 | 0.00 |
| Belgium | **0.97** | 0.00 | 0.03 | **0.61** | 0.00 | 0.02 | 0.37 | **0.61** | 0.00 | 0.02 | 0.36 | 0.00 |
| Bulgaria | 0.12 | 0.00 | **0.88** | 0.05 | 0.00 | **0.89** | 0.06 | 0.06 | 0.00 | 0.10 | 0.06 | **0.79** |
| Croatia | 0.35 | 0.01 | **0.64** | 0.30 | 0.01 | **0.43** | 0.26 | 0.05 | 0.00 | **0.89** | 0.04 | 0.02 |
| Czech Republic | 0.45 | 0.00 | **0.55** | **0.41** | 0.00 | 0.28 | 0.31 | **0.41** | 0.00 | 0.13 | 0.32 | 0.13 |
| Denmark | **0.96** | 0.00 | 0.04 | **0.92** | 0.00 | 0.01 | 0.06 | **0.92** | 0.00 | 0.02 | 0.06 | 0.00 |
| Estonia | 0.01 | **0.98** | 0.01 | 0.01 | **0.97** | 0.01 | 0.01 | 0.01 | **0.97** | 0.01 | 0.01 | 0.00 |
| Finland | **0.75** | 0.03 | 0.22 | **0.76** | 0.02 | 0.09 | 0.13 | **0.60** | 0.01 | 0.25 | 0.11 | 0.03 |
| France | **0.99** | 0.00 | 0.01 | **0.90** | 0.00 | 0.01 | 0.10 | **0.92** | 0.00 | 0.01 | 0.08 | 0.00 |
| Germany | **0.76** | 0.00 | 0.24 | **0.84** | 0.00 | 0.07 | 0.09 | **0.76** | 0.00 | 0.14 | 0.09 | 0.02 |
| Greece | 0.41 | 0.02 | **0.57** | 0.20 | 0.01 | 0.27 | **0.52** | 0.18 | 0.01 | 0.21 | **0.43** | 0.17 |
| Hungary | **0.94** | 0.00 | 0.06 | **0.79** | 0.00 | 0.02 | 0.19 | **0.77** | 0.00 | 0.04 | 0.18 | 0.01 |
| Ireland | **0.52** | 0.05 | 0.43 | 0.31 | 0.03 | 0.21 | **0.45** | 0.26 | 0.03 | 0.17 | **0.40** | 0.14 |
| Italy | **0.98** | 0.00 | 0.02 | **0.89** | 0.00 | 0.01 | 0.10 | **0.88** | 0.00 | 0.02 | 0.10 | 0.00 |
| Latvia | 0.00 | **0.99** | 0.00 | 0.00 | **0.99** | 0.00 | 0.00 | 0.00 | **0.99** | 0.00 | 0.00 | 0.00 |
| Lithuania | 0.04 | **0.91** | 0.05 | 0.05 | **0.86** | 0.06 | 0.03 | 0.05 | **0.77** | 0.11 | 0.03 | 0.04 |
| Netherlands | **0.97** | 0.00 | 0.03 | **0.86** | 0.00 | 0.01 | 0.13 | **0.87** | 0.00 | 0.01 | 0.12 | 0.00 |
| Norway | **0.82** | 0.00 | 0.18 | 0.37 | 0.00 | 0.07 | **0.55** | 0.38 | 0.00 | 0.10 | **0.50** | 0.03 |
| Poland | **0.89** | 0.00 | 0.11 | 0.27 | 0.00 | 0.03 | **0.70** | 0.26 | 0.00 | 0.04 | **0.69** | 0.01 |
| Portugal | **0.79** | 0.00 | 0.20 | 0.11 | 0.00 | 0.02 | **0.86** | 0.11 | 0.00 | 0.03 | **0.86** | 0.01 |
| Romania | 0.17 | 0.02 | **0.82** | 0.08 | 0.01 | **0.81** | 0.10 | 0.01 | 0.00 | 0.02 | 0.01 | **0.96** |
| Slovakia | 0.16 | 0.01 | **0.83** | 0.14 | 0.01 | **0.74** | 0.11 | 0.02 | 0.00 | **0.94** | 0.02 | 0.02 |
| Slovenia | 0.23 | 0.01 | **0.76** | 0.31 | 0.01 | **0.53** | 0.16 | 0.21 | 0.00 | **0.59** | 0.11 | 0.07 |
| Spain | **0.74** | 0.00 | 0.26 | 0.03 | 0.00 | 0.01 | **0.96** | 0.03 | 0.00 | 0.01 | **0.96** | 0.00 |
| Sweden | **0.90** | 0.00 | 0.09 | **0.82** | 0.00 | 0.03 | 0.15 | **0.78** | 0.00 | 0.06 | 0.15 | 0.01 |
| Switzerland | **0.93** | 0.00 | 0.07 | **0.72** | 0.00 | 0.03 | 0.24 | **0.74** | 0.00 | 0.03 | 0.21 | 0.01 |
| United Kingdom | **0.96** | 0.00 | 0.03 | **0.81** | 0.00 | 0.02 | 0.18 | **0.80** | 0.00 | 0.04 | 0.16 | 0.00 |
| | **Sample average silhouette** 0.3974 | | | **Sample average silhouette** 0.3301 | | | | **Sample average silhouette** 0.3212 | | | | |

Notes: The table summarizes the cluster results of our FCM approach of CF-filtered quarterly real GDP (1996 Q1–2015 Q4; m=1.5; c from 3 to 5). The values express relative membership of each cluster ($u_{ij}$). The highest cluster membership is signified by bold letters.

The second business cycle cluster to be found in all the specifications consists of the Baltic states of Estonia (0.97–0.98), Latvia (0.99) and Lithuania (0.77–0.91).[9] The high membership coefficients indicate that these countries form a very distinct cluster in which the centroid apparently lies the furthest away from all the others. The third cluster, which we label the eastern periphery, comprises Croatia (0.43–0.89), Slovakia (0.74–0.94) and Slovenia (0.53–0.76) in each cluster solution. When the number of clusters is increased to four, the southern periphery – previously part of the core – is made up of Portugal (0.86) and Spain (0.96), joined by countries with lower membership coefficients, such as Poland (0.70), Norway (0.55), Greece (0.52) and Ireland (0.45). This composition might be due to the recent crisis experience of the so-called GIPS countries, which will be controlled for below. Remarkably, the membership coefficients of the latter two countries as well as that of the Czech Republic do not significantly exceed 0.5. They can thus be considered as outliers that are not clearly assigned to one of the business cycle clusters. Finally, Bulgaria and Romania, which have so far been part of the eastern periphery, form a distinct cluster at $c$=5.

The documented results reveal that the core–periphery pattern among European business cycles is complex. Any study that explicitly divides the sample into a core group on the one hand and a peripheral group on the other oversimplifies the group structure of European business cycles that is revealed

[9] In the two-cluster solution, which is not depicted here, the country sample is always divided into a cluster containing the Baltics and another cluster comprising all the other countries.

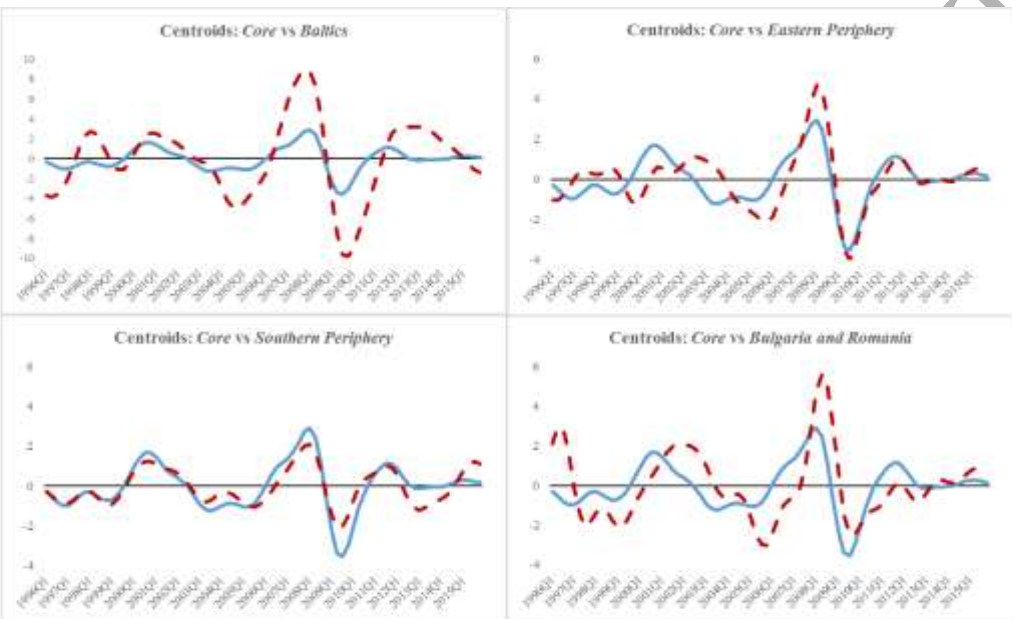
by the fuzzy clustering. First, the membership matrix shows that – apart from Hungary and to a lesser degree Poland and the Czech Republic – most CEECs have a rather low degree of business cycle synchronization with the European core. This confirms the results of Kolasa (2013), Stanisic (2013) and Di Giorgio (2016), who find a low synchronization between CEECs and the EA. Second, however, they do not constitute a homogeneous group of synchronized countries. Our results reveal a great deal of heterogeneity among the CEECs, as they split up into three different business cycle clusters at $c=5$. Hence, any study of European business cycle synchronization that includes the CEECs should take this heterogeneity into account. Third, our result of a separate southern periphery cluster around Spain and Portugal contradicts the findings of previous studies investigating the pre-euro crisis period, in which a high degree of synchronization between the European core and these countries is detected (see, e.g., Camacho et al. 2006 and 2008; Pentecôte and Huchet-Bourdon 2012; Aguiar-Conraria et al. 2013; Lehwald 2013). The finding is in line with more recent studies of the post-crisis period (Gächter et al. 2012; Ferroni and Klaus 2013; Degiannakis et al. 2014; Belke et al. 2016) that assign the two countries to the southern periphery. We will discuss this issue further in the context of the crisis impacts below. Furthermore, the inclusion of Ireland and Greece in this group (as undertaken by various studies analyzing the core vs. the GIPS, e.g. Lehwald 2013; Caporale et al. 2015; Arestis and Phelps 2016; Belke et al. 2016) might be problematic, as our results indicate that these two countries constitute outliers and may, if included in any business cycle group, drive the results due to their very idiosyncratic development.

According to the OCA literature, an ideal monetary union would consist of countries with synchronized business cycles. Hence, since all the members of the clusters that we identify exhibit a high degree of business cycle similarity, these clusters would qualify as separate OCAs, at least in terms of business cycle synchronization. In reality, of course, more is involved in determining the costs of sharing a currency. However, as the countries of the core are the economically and politically powerful leaders of the European integration process (and most of them have already adopted the euro), the European core business cycle obviously represents the only feasible anchor for current and prospective members of the monetary union. The membership coefficients thus allow for inference on the costs of being a member of the EA. In this regard the adoption of the euro in the 'opt out' countries of Denmark, Sweden and the UK, as well the 'EU out' Switzerland, would be unproblematic, a result that supports the finding of the multivariate cluster analysis by Wortmann and Stahl (2016). The same holds for Hungary, since it is, as described, the only CEEC that is unambiguously a member of the core. In contrast, other CEECs that are not yet part of the EA, such as Bulgaria, Croatia and Romania, show very low membership coefficients of the core, signifying high potential costs of EA accession. Several countries that have already adopted the euro unfortunately share this pattern, for example the Baltics, Slovakia and Slovenia or countries on the southern periphery, such as Portugal or Spain. In line with the findings of Wortmann and Stahl (2016), this demonstrates that the current composition of the EA is far from optimal. The countries that could share a common currency with the core are not members of the EA, while others are part of the EA although membership appears to be costly.

### 3.2. The relationship between core and peripheral business cycles

Having defined the overall degree of belongingness that each country exhibits to the different clusters, we now examine the relationship between the group-specific centroid cycles (Figure 1). A visual inspection of the four peripheral business cycles in comparison with the core cycle allows the first conclusions about the drivers of our clustering results from the previous section. Compared with the core, the Baltics apparently have business cycles with a much higher amplitude, especially (but not exclusively) during the immediate crisis period of 2008/2009. The eastern periphery, on the other hand, appears to be largely asynchronous with the core before the global financial crisis, while the amplitude was comparable. Since the crisis, however, the core and the eastern periphery have apparently shared largely similar output gaps. The opposite seems to be the case for the southern periphery. Its business cycle was apparently very synchronized with the core before the crisis and has increasingly differed since 2009 (e.g. due to a less severe immediate crisis experience and the 'double-dip' recession). To investigate this relation between the clusters further, we use the European core business cycle of the FCM analysis as a reference cycle for three time-varying synchronization measures.

**Figure 1: Cluster Centroids**




Notes: The figure depicts the respective cluster centroids (dashed lines) compared with the centroids of the core cluster (dotted lines) based on the FCM solution for c=5 and m=1.5 over the period 1996 Q1–2015 Q4.

First, we compute the *time-varying correlation coefficient* $\rho_{i,r}(t)$, as proposed by Cerqueira and Martins (2009) and Cerqueira (2013), between the time series of the four peripheral clusters and the core time series.[10] Furthermore,

[10] The correlation between time series $g_i$ and reference series $g_r$ is calculated at each point in time using the following formula: $\rho_{i,r}(t) = 1 - \frac{1}{2}\left(\frac{g_{i,t}-\bar{g}_i}{\sqrt{\frac{1}{T}\sum_{t=1}^{T}\left(g_{i,t}-\bar{g}_i\right)^2}} - \frac{g_{r,t}-\bar{g}_r}{\sqrt{\frac{1}{T}\sum_{t=1}^{T}\left(d_{r,t}-\bar{d}_r\right)^2}}\right)^2$. The average of $\rho_{i,r}(t)$ over t yields the correlation coefficient between the two time series. Several authors use this measure in their studies of business cycle synchronization in Europe. For instance, Gächter and Riedl (2014) compute pair-wise correlations for their sample countries, while Belke et al. (2016) additionally use time-varying correlations with an EA(12) reference time series.

we follow Mink et al. (2012) in distinguishing between two aspects of business cycle synchronization that overlap when only the correlation coefficient between two time series is used. They suggest involving both *business cycle synchronicity* $\varphi_{ir}(t)$, that is, if the two time series of interest are in the same phase of the business cycle, and *business cycle similarity* $\gamma_{ir}(t)$ to compare the amplitudes of the two business cycles.[11] Figure 2 compares the three-year moving average[12] of these measures for all four cluster centroids with the core time series as a reference. This allows us to draw several conclusions.

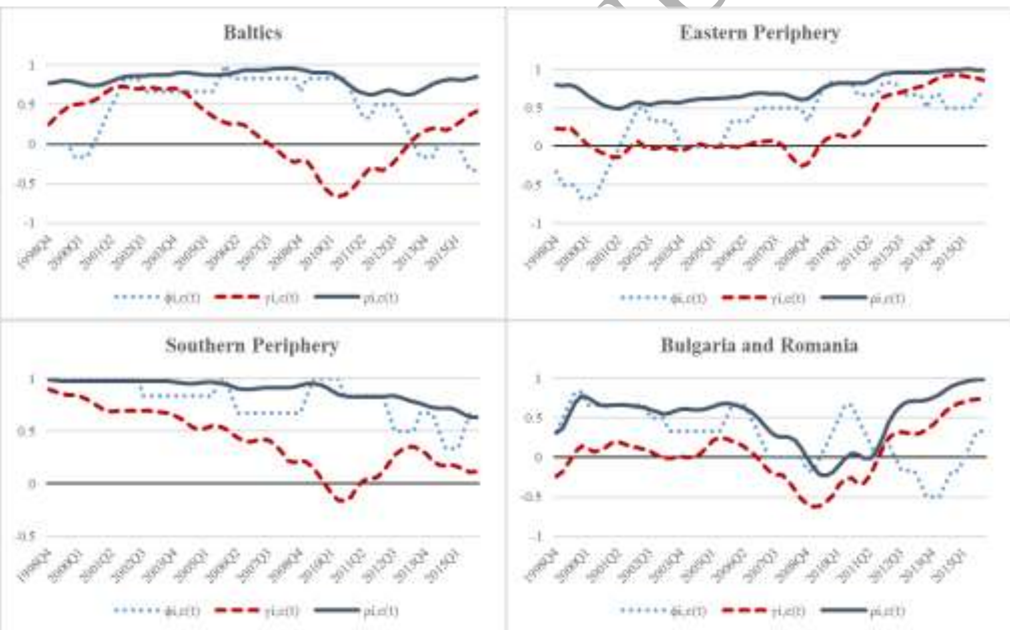
First, the Baltics have a high correlation with the core time series (an overall correlation coefficient of 0.88), which is around 0.9 for most of the time period. This is remarkable, as our cluster results show that the Baltics form a very distinct business cycle cluster. The values for *business cycle synchronicity* and s*imilarity* offer an explanation for this discrepancy and confirm our suspicion mentioned above. While the timing of the up- and downswings of the core and Baltic business cycles coincide (indicated by high *synchronicity*), their amplitudes differ widely, which explains the clear

[11] Business cycle synchronicity $\phi_{ir}(t)$ and business cycle similarity $\gamma_{ir}(t)$ between time series $g_i$ and reference series $g_r$ are defined as: $\phi_{ir}(t) = \frac{g_i(t)g_r(t)}{|g_i(t)g_r(t)|}$ ; $\gamma_{ir}(t) = 1 - \frac{|g_i(t)-g_r(t)|}{\sum_{i=1}^{n}|g_i(t)|/n}$

[12] As we are rather interested in the trends of business cycle synchronization than in short-term developments, we concentrate on three-year moving averages. In fact, when depicting the indicators of Mink et al. (2012) short-term fluctuations might dominate the figure if the quarterly time series were used, especially when the compared output gaps are close to zero. Particularly the binary synchronization indicator is thus less appropriate if not used with moving averages.

distinction between the Baltics and the core in the clustering. From about 2004 onwards (i.e. since the Baltics' EU accession), a clear trend of less similar business cycles, at least in terms of amplitude, is observable. Hence, the business cycle of the Baltics shows an ambivalent relation to the core: temporal accordance but large differences in amplitude. Since the end of the global financial crisis around 2010, this relationship has changed, with increasing *similarity* and decreasing s*ynchronicity* between the Baltics and the core.

**Figure 2: Relation of the Peripheral Business Cycles to the Core**




Notes: The figure depicts the relation between the centroids of the four peripheral clusters and the core. This relation is measured using the following variables (1) $\varphi_{i,C}(t)$: business cycle synchronicity (dotted lines), (2) $\gamma_{i,C}(t)$: business cycle similarity (dashed lines) and (3) $\rho_{i,C}(t)$: time-varying correlation (straight lines). In this case *i* denotes the respective cluster in comparison with the centroid time series of the core, denoted by C.

Second, the business cycle of the eastern periphery relates differently to the core. The correlation between the two time series remained rather low between the mid-1990s and the onset of the financial crisis. Hence, the two business cycles were largely asynchronous, as further indicated by both low *similarity* and low *synchronicity* during that time period. From 2009 onwards, however, this relationship changed. Apparently, the business cycles of the eastern periphery and the core converged in the aftermath of the global financial crisis: the correlation, *similarity* and (to a lesser extent) *synchronicity* increased strongly. The business cycle of the cluster around Bulgaria and Romania developed differently. Their already-low correlation with the core time series declined significantly between 2006 and 2010. Since then the *similarity* and correlation have increased while the *synchronicity* has remained low.

The convergence of most clusters among the CEECs towards the core confirms the findings of previous studies on business cycle synchronization that detect the convergence of these countries (at least) since the global financial crisis as well (see Kolasa 2013; Stanisic 2013; Di Giorgio 2016). Still, there is a high degree of heterogeneity in these developments among the CEECs. The eastern periphery relates differently to the core from the Baltics, which in turn differ significantly from outlier countries like Romania, Bulgaria and the Czech Republic or Hungary.

Third, the business cycle of the southern periphery exhibits yet another development in its relation to the core. Between the mid-1990s and circa 2010, the two time series correlated strongly, while the *synchronicity* measure showed coinciding up- and downswings. From the early 2000s onwards, however, the amplitudes of the two business cycles differed increasingly, while the same holds for correlation and *synchronicity* since 2009. Obviously, the business cycles of the core and the southern periphery have diverged since the global financial crisis. This divergence in the aftermath of the crisis seems to have driven our clustering results. This is in line with studies focusing on the pre-crisis period and detecting a high degree of synchronization between the southern periphery and the core during that time (Camacho et al. 2006 and 2008; Aguiar-Conraria and Soares 2011; Pentecôte and Huchet-Bourdon 2012; Aguiar-Conraria et al. 2013; Lehwald 2013) but also confirms the findings of studies that include the post-crisis period (Gächter et al. 2012; Ferroni and Klaus 2013; Degiannakis et al. 2014; Belke et al. 2016). The divergence since 2008 can be seen in the context of the unwinding of the economic balances that piled up in the pre-crisis period and led to the 'euro crisis' in southern Europe (Baldwin et al. 2015). Simultaneous fiscal and banking crises produced the need for deleveraging in both the public and the private sector, reinforcing the growth crisis in these countries and triggering the divergence of the cyclical fluctuations between the southern periphery and the core (European Commission 2014).[13]

[13]As the focus of the present paper lies on assessing the group pattern of European business

### 3.3. The core and periphery before and after the crisis

Our analysis above shows that the relationship between the peripheral business cycle clusters and the core exhibits profound changes between the time period before and that after the crisis. To check whether our overall cluster solutions are robust with respect to these differences and whether the trends that we identify can be confirmed, we split the time period into a pre-crisis (1996 Q1–2007 Q4) and a post-crisis period (2008 Q1–2015 Q4). We then conduct separate FCM analyses for each period and present those solutions in Table 2 that result in the highest average silhouette at different values of *c*.

The first point to notice here is that the silhouette values indicate two different numbers of clusters for the two time periods: in the pre-crisis period a four-cluster solution is superior, while in the post-crisis period $c=3$ is the preferred partition. A core cluster is identified in both periods as well as a cluster around the Baltics (consisting only of Estonia and Latvia in the first period). The composition of the remaining peripheral clusters, however, changes. While in the pre-crisis period two separate clusters on the eastern periphery are identified (one around the Czech Republic; the other around Croatia and

cycles, we do not explicitly analyze potential driving forces behind these developments. There is, however, a large literature dealing with possible determinants of business cycle synchronization (for a survey, see De Haan 2008). Primarily, the role of trade linkages has been studied (see, for instance, Inklaar et al. 2008 and Gächter, and Riedl 2014), but other dimensions, such as the effects of EU and EA membership per se, have been investigated as well (Goncalves et al. 2009, Christodoulopoulou 2014, Gächter and Riedl 2014 or Bierbaumer-Polly et al. 2016). In a more recent study, Gächter et al. (2017) analyze the role of wage developments. They find that wage growth divergence led to a reduction of business cycle co-movement within the EA, which might be one explanation for the diverging patterns we find between the core and the southern periphery.

Romania), no such cluster is evident after the crisis at *c=3*. Instead, most countries of the former eastern peripheries enter the core cluster, indicating greater proximity than in the first period.[14] The clear separation between the CEECs and the rest of Europe in the pre-crisis period is in line with the findings of Camacho et al. (2006 and 2008), who detect such a division with their cluster analyses. In their analysis of data between 1990 and 2003, the CEECs constitute separate clusters, while the southern European countries are part of an EU15 cluster.

Our sample split analysis, however, shows that this pattern has changed, as, in the second period, the southern periphery cluster is formed around Portugal and Spain, while most of the CEECs enter the core. These results confirm our findings reported above, as the global financial crisis apparently constitutes a structural break in the relationship between the European core and the periphery. Since then the eastern periphery has converged towards the core while the southern periphery has diverged, forming a separate cluster. Another remarkable development can be seen for Belgium, Italy and France. All three countries show very high membership coefficients of the core in the first

[14] If, however, the inferior four-cluster solution (silhouette value of 0.29) is used in the second period, an eastern periphery (including Germany to a high degree) appears again. Therefore, despite having core membership coefficients between 0.11 and 0.39, this country group cannot be regarded as being completely integrated into the core cluster. All the cluster solutions are available on request.

period. Conversely, in the second period, they belong to the southern periphery to a high degree (Belgium even switches membership).[15]



[15] Our robustness checks, however, show that these results disappear for Belgium and France when the immediate crisis periods are omitted from the analysis. The result for Italy remains robust (see below).

**Table 2: Pre- and Post-Crisis FCM Results (Period 1: 1996 Q1–2007 Q4; Period 2: 2008 Q1–2015 Q4)**

| | First Period (1996 Q1–2007 Q4) | | | | Second Period (2008 Q1–2015 Q4) | | |
|---|---|---|---|---|---|---|---|
| ***m=1.7*** ***CF Filtered Data*** | Cluster 1: Core | Cluster 2: Baltics | Cluster 3: Eastern Periphery | Cluster 4: South Eastern Periphery | Cluster 1: Core | Cluster 2: Baltics | Cluster 3: Southern Periphery |
| Austria | **0.97** | 0.00 | 0.02 | 0.01 | **0.90** | 0.00 | 0.10 |
| Belgium | **0.88** | 0.00 | 0.07 | 0.05 | 0.44 | 0.00 | **0.56** |
| Bulgaria | 0.18 | 0.01 | **0.64** | 0.16 | **0.66** | 0.02 | 0.31 |
| Croatia | 0.06 | 0.01 | 0.03 | **0.90** | **0.87** | 0.01 | 0.12 |
| Czech Republic | 0.09 | 0.01 | **0.87** | 0.03 | **0.65** | 0.00 | 0.34 |
| Denmark | **0.84** | 0.01 | 0.10 | 0.04 | **0.88** | 0.00 | 0.11 |
| Estonia | 0.02 | **0.95** | 0.01 | 0.02 | 0.03 | **0.95** | 0.02 |
| Finland | **0.80** | 0.02 | 0.09 | 0.10 | **0.74** | 0.08 | 0.17 |
| France | **0.98** | 0.00 | 0.01 | 0.00 | **0.65** | 0.00 | 0.34 |
| Germany | **0.52** | 0.01 | 0.38 | 0.09 | **0.93** | 0.00 | 0.07 |
| Greece | 0.15 | 0.01 | 0.11 | **0.73** | 0.33 | 0.04 | **0.63** |
| Hungary | **0.89** | 0.01 | 0.06 | 0.05 | **0.81** | 0.00 | 0.19 |
| Ireland | 0.24 | 0.02 | **0.69** | 0.06 | 0.38 | 0.09 | **0.53** |
| Italy | **0.92** | 0.00 | 0.05 | 0.03 | **0.65** | 0.01 | 0.34 |
| Latvia | 0.01 | **0.96** | 0.01 | 0.01 | 0.02 | **0.97** | 0.01 |
| Lithuania | 0.18 | 0.26 | 0.13 | **0.43** | 0.03 | **0.96** | 0.02 |
| Netherlands | **0.94** | 0.00 | 0.05 | 0.01 | **0.80** | 0.00 | 0.20 |
| Norway | **0.79** | 0.01 | 0.09 | 0.11 | 0.39 | 0.01 | **0.59** |
| Poland | **0.75** | 0.01 | 0.13 | 0.11 | 0.22 | 0.00 | **0.78** |
| Portugal | **0.77** | 0.01 | 0.12 | 0.11 | 0.15 | 0.00 | **0.85** |
| Romania | 0.17 | 0.03 | **0.61** | 0.20 | **0.54** | 0.08 | 0.38 |
| Slovakia | 0.05 | 0.01 | 0.05 | **0.89** | **0.83** | 0.02 | 0.16 |
| Slovenia | 0.30 | 0.02 | **0.45** | 0.23 | **0.75** | 0.03 | 0.22 |
| Spain | **0.66** | 0.00 | 0.25 | 0.08 | 0.03 | 0.00 | **0.97** |
| Sweden | **0.87** | 0.01 | 0.08 | 0.04 | **0.65** | 0.02 | 0.32 |
| Switzerland | **0.88** | 0.00 | 0.09 | 0.03 | **0.62** | 0.01 | 0.38 |
| United Kingdom | **0.89** | 0.00 | 0.05 | 0.05 | **0.73** | 0.00 | 0.27 |
| | **Sample average silhouette** 0.5382 | | | | **Sample average silhouette** 0.4473 | | |

Notes: The table summarizes the cluster results of our FCM approach of CF-filtered quarterly real GDP for two separate time periods: 1996 Q1–2007 Q4 as the first and 2008 Q1–2015 Q4 as the second period. The values again express relative membership of each cluster ($u_{ij}$). The highest cluster membership is signified by bold letters.

### 3.4 Robustness analysis

The results of a cluster analysis can be sensitive to the specifications used, such as the selected variables and objects, the distance measures and the clustering algorithms. Hence, we conduct several additional analyses to test the robustness of our main results. Specifically, (1) we vary the filtering method that we employ to extract the output gaps from the GDP series, (2) we expand our country sample with additional OECD countries, (3) we employ an additional hierarchical clustering algorithm, (4) we repeat the main FCM analysis with a different distance measure and (5) we exclude the years of the immediate crisis impact, 2008/2009, from our sample split analysis. All five robustness checks confirm our main results.

The first robustness check is concerned with the filtering of the original data. In all the main analyses, we employ the band-pass filter of Christiano and Fitzgerald (2003). Table A1 in the appendix summarizes the results of our cluster analyses, which are based on output gaps that have been extracted using the high-pass filter of Hodrick and Prescott (1997). In line with the former results, we find a stable core cluster opposed to peripheral clusters that form when the number of clusters is increased. At $c=3$ the country sample is divided into the core, the Baltics and the eastern periphery. While at $c=4$ the southern periphery is separated from the core, at $c=5$ an outlier cluster forms around Romania and (now to a lesser degree) Bulgaria. The composition of the clusters remains stable as well. The only exception is the southern periphery, since Poland and Norway are members of the core (albeit with rather low membership coefficients) and Portugal shows a lower membership degree of this cluster at *c=5*. Apart from these deviations, however, the main results are robust to this change in the filtering method.

The same holds for a variation of the country sample. To check whether such a variation changes our cluster membership, we include three additional non-European industrialized OECD countries (Japan, South Korea and the United States). The results are presented in Appendix Table A2. We detect a core cluster opposed to clusters on the eastern and southern peripheries and a cluster containing the Baltic States. The latter cluster, however, changes at *c=5*, as Lithuania now constitutes an outlier cluster as opposed to Bulgaria and/or Romania previously. This result might be driven by differences between Lithuania and the other two Baltic States in the pre-crisis period, as indicated by our results from the sample split. The US and Japan enter the core cluster, while Korea switches membership at different values of *c* and hence constitutes an outlier. These results for the US and Japan are quite interesting, as they indicate a high degree of business cycle synchronization among fully developed industrial nations, regardless of their regional proximity, as for example is also found by Lehwald (2013), who conducts a similar robustness check.

In addition to these variations of the filtering and the country sample, we employ a different clustering algorithm and distance measure. Although in our view a partitional clustering algorithm such as FCM is better suited to our purposes, we compare our findings with those arising from hierarchical clustering (weighted average linkage[16]). The results are depicted in a dendrogram (Figure A1 in the Appendix) indicating that the overall composition of our clusters does not change. The core cluster is the most obvious group with the smallest within-cluster differences and comprises exactly those twelve countries that centered the core cluster in our main analysis. The results for the remaining clusters resemble our findings as well. The Baltics constitute a separate cluster, furthest away from all the others and exhibiting considerable heterogeneity within the cluster (especially regarding Lithuania). Furthermore, the hierarchical analysis confirms the existence of clusters on the southern (again comprising Spain and Portugal as well as Poland and Norway) and the eastern periphery (several clusters comprising Bulgaria and Romania, Croatia and Slovakia, and the Czech Republic and Slovenia) and confirms that Greece and Ireland constitute outliers. As the second variation of our clustering method, we repeat our FCM analysis with another distance measure (Manhattan distance, Table A4) and are again able to reproduce our main results. Apart from smaller deviations in the membership coefficients, the cluster structure and membership resemble our findings, as

[16] We choose the weighted average linkage method as it constitutes a compromise between hierarchical methods on the spectrum between the ‘nearest-neighbor’ method (single linkage) and the ‘furthest-neighbor’ method (complete linkage, Hastie et al. 2008). The results for other hierarchical clustering algorithms, however, are in line with our main analysis as well and are available on request.

we again detect a stable cluster around the twelve core countries, opposed to the Baltics and the eastern and southern peripheries.

Lastly, we repeat our sample split analysis and exclude the years 2008 and 2009 to check whether the immediate crisis impact drives our results for the second (post-crisis) period. That, however, is not the case. The silhouette again indicates that the three-cluster solution is superior for the post-crisis period. In this solution most countries from the eastern periphery again join the core cluster while the southern periphery cluster is separated from that core. Hence, the main finding of the sample split analysis – convergence of the eastern and divergence of the southern periphery – is confirmed. The results for France and Belgium, however, change, as they are now again unambiguous members of the core cluster. The similar result for Italy, however, remains robust, since its membership of the core remains rather low, signifying proximity to the southern periphery in the post-crisis period.

## 4. Conclusion

The recent euro crisis has underlined the need to address European business cycle patterns from a country group perspective. Previous research often uses the distinction between the core and the periphery either to analyze cyclical synchronization in arbitrarily predefined groups or to classify countries' synchronicities with respect to several reference measures. Differently from these studies, we propose a time series fuzzy clustering approach to assess the core–periphery pattern empirically in a direct manner that does not require strict assumptions. By applying the FCM clustering algorithm to output gap series of 27 European countries, we identify a core group consisting of Central European countries opposed to several clusters on the eastern and southern European peripheries along with the representative group-specific European business cycles. Both the classification and the obtained reference cycles may be used by the literature dealing with business cycle synchronization. For instance, the detected European core business cycle can be regarded as an anchor cycle for all countries wishing to share a common currency with the core countries (which mostly have already adopted the euro). We find evidence against using Germany's business cycle as a proxy for that cycle, as other core countries, like France, follow the European core business cycle more closely. Remarkably, this is also true for Italy, which is sometimes classified as belonging to the southern European periphery.

By quantifying each country's degree of belongingness to all the clusters, our analysis provides useful information about the cyclical suitability of individual countries for monetary unification with the core. While there is certainly more involved in the decision to enter the EA, the 'EA' and 'EU outs,' Denmark, Sweden, Switzerland and the UK, as well as some CEECs, especially Hungary and to a lesser degree the Czech Republic and Poland, could adopt the euro at a lower cost than the other countries on the eastern or southern European periphery. However, while some non-EA members clearly belong to the core, several peripheral countries with less synchronized cycles have adopted the euro instead (especially Greece, Ireland, Portugal and Spain). If the EA persists in its current composition, a common monetary policy and exchange rate are thus likely to remain costly for several members. Conversely, our results show that there are country groups in Europe that qualify as separate OCAs in terms of business cycle similarities. This pattern, however, changes over time. Our findings reveal that, while many CEECs converge towards the core, the southern periphery primarily around Spain and Portugal shows some divergence since the global financial crisis. Obviously, the driving forces behind these developments are of great interest to scholars and policy makers alike and constitute an interesting topic for future research.

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## Appendix

**Table A1: FCM Results, Output Gaps Extracted Using the Hodrick–Prescott Filter (Whole Period 1996 Q1–2015 Q4)**

| | **3-Cluster Solution** | | | **4-Cluster Solution** | | | | **5 -Cluster Solution** | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| ***m=1.5 HP Filtered Data*** | ***Cluster 1 Core*** | *Cluster 2: Baltics* | *Cluster 3: Eastern P.* | ***Cluster 1 Core*** | *Cluster 2: Baltics* | *Cluster 3: Eastern P.* | *Cluster 4: Southern P.* | ***Cluster 1 Core*** | *Cluster 2: Baltics* | *Cluster 3: Eastern P.* | *Cluster 4: Southern P.* | *Cluster 5: Bul. & Rom.* |
| Austria | **0.98** | 0.00 | 0.02 | **0.97** | 0.00 | 0.01 | 0.03 | **0.95** | 0.00 | 0.01 | 0.04 | 0.00 |
| Belgium | **0.98** | 0.00 | 0.02 | **0.95** | 0.00 | 0.01 | 0.04 | **0.92** | 0.00 | 0.01 | 0.07 | 0.00 |
| Bulgaria | 0.31 | 0.05 | **0.64** | 0.19 | 0.03 | **0.50** | 0.27 | 0.13 | 0.02 | 0.21 | 0.17 | **0.47** |
| Croatia | 0.23 | 0.02 | **0.75** | 0.12 | 0.01 | **0.66** | 0.20 | 0.06 | 0.01 | **0.79** | 0.08 | 0.06 |
| Czech Republic | 0.38 | 0.00 | **0.61** | 0.13 | 0.00 | 0.11 | **0.77** | 0.15 | 0.00 | 0.12 | **0.67** | 0.06 |
| Denmark | **0.95** | 0.00 | 0.05 | **0.85** | 0.00 | 0.03 | 0.12 | **0.80** | 0.00 | 0.04 | 0.16 | 0.01 |
| Estonia | 0.01 | **0.97** | 0.01 | 0.01 | **0.96** | 0.01 | 0.01 | 0.01 | **0.95** | 0.02 | 0.01 | 0.01 |
| Finland | **0.81** | 0.01 | 0.18 | **0.66** | 0.01 | 0.11 | 0.22 | **0.55** | 0.01 | 0.20 | 0.21 | 0.03 |
| France | **0.99** | 0.00 | 0.01 | **0.97** | 0.00 | 0.00 | 0.02 | **0.96** | 0.00 | 0.00 | 0.03 | 0.00 |
| Germany | **0.93** | 0.00 | 0.06 | **0.86** | 0.00 | 0.03 | 0.10 | **0.81** | 0.00 | 0.05 | 0.12 | 0.01 |
| Greece | 0.24 | 0.02 | **0.74** | 0.15 | 0.01 | **0.46** | 0.37 | 0.13 | 0.01 | 0.26 | 0.28 | **0.33** |
| Hungary | **0.61** | 0.01 | 0.38 | 0.38 | 0.00 | 0.18 | **0.44** | 0.35 | 0.00 | 0.19 | **0.39** | 0.06 |
| Ireland | 0.38 | 0.08 | 0.53 | 0.23 | 0.05 | 0.26 | **0.45** | 0.20 | 0.05 | 0.22 | **0.36** | 0.18 |
| Italy | **0.98** | 0.00 | 0.02 | **0.90** | 0.00 | 0.01 | 0.09 | **0.84** | 0.00 | 0.02 | 0.14 | 0.00 |
| Latvia | 0.01 | **0.98** | 0.01 | 0.01 | **0.98** | 0.01 | 0.01 | 0.01 | **0.97** | 0.01 | 0.01 | 0.01 |
| Lithuania | 0.03 | **0.93** | 0.04 | 0.03 | **0.88** | 0.06 | 0.03 | 0.03 | **0.82** | 0.08 | 0.03 | 0.04 |
| Netherlands | **0.95** | 0.00 | 0.05 | **0.81** | 0.00 | 0.02 | 0.17 | **0.66** | 0.00 | 0.03 | 0.30 | 0.01 |
| Norway | **0.82** | 0.01 | 0.18 | **0.66** | 0.01 | 0.11 | 0.23 | 0.57 | 0.00 | 0.12 | 0.26 | 0.04 |
| Poland | **0.88** | 0.00 | 0.12 | **0.72** | 0.00 | 0.06 | 0.21 | **0.61** | 0.00 | 0.08 | 0.28 | 0.02 |
| Portugal | **0.80** | 0.00 | 0.19 | **0.49** | 0.00 | 0.08 | 0.43 | 0.34 | 0.00 | 0.07 | **0.56** | 0.03 |
| Romania | 0.18 | 0.03 | **0.79** | 0.09 | 0.02 | **0.70** | 0.19 | 0.02 | 0.00 | 0.04 | 0.02 | **0.92** |
| Slovakia | 0.29 | 0.04 | **0.67** | 0.16 | 0.02 | **0.60** | 0.21 | 0.08 | 0.01 | **0.73** | 0.09 | 0.08 |
| Slovenia | 0.24 | 0.01 | **0.75** | 0.16 | 0.01 | 0.36 | **0.48** | 0.13 | 0.00 | **0.47** | 0.31 | 0.09 |
| Spain | **0.56** | 0.00 | 0.44 | 0.06 | 0.00 | 0.02 | **0.91** | 0.03 | 0.00 | 0.01 | **0.95** | 0.00 |
| Sweden | **0.91** | 0.00 | 0.09 | **0.74** | 0.00 | 0.04 | 0.21 | **0.66** | 0.00 | 0.07 | 0.26 | 0.01 |
| Switzerland | **0.97** | 0.00 | 0.03 | **0.92** | 0.00 | 0.02 | 0.06 | **0.88** | 0.00 | 0.02 | 0.10 | 0.01 |
| United Kingdom | **0.91** | 0.00 | 0.09 | **0.79** | 0.00 | 0.05 | 0.16 | **0.72** | 0.00 | 0.07 | 0.19 | 0.02 |
| | **Sample average silhouette** 0.4363 | | | **Sample average silhouette** 0.3517 | | | | **Sample average silhouette** 0.2955 | | | | |

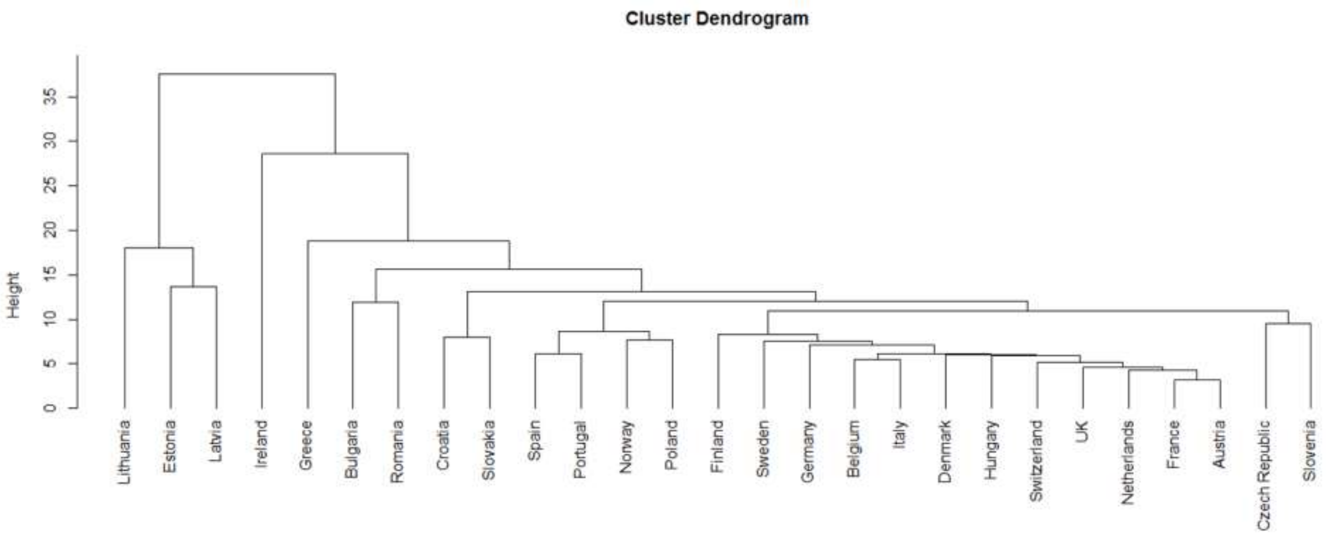
Notes: The table summarizes the cluster results of our FCM approach of HP-filtered quarterly real GDP (1996 Q1–2015 Q4; m=1.5; c from 3 to 5). The values express relative membership of each cluster ($u_{ij}$). The highest cluster membership is signified by bold letters.

**Table A2: FCM Results, Including the USA, Japan and Korea (Whole Period 1996 Q1–2015 Q4)**

| | **3-Cluster Solution** | | | **4-Cluster Solution** | | | | **5 -Cluster Solution** | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| ***m=1.5 CF Filtered Data*** | ***Cluster 1 Core*** | *Cluster 2: Baltics* | *Cluster 3: Eastern P.* | ***Cluster 1 Core*** | *Cluster 2: Baltics* | *Cluster 3: Eastern P.* | *Cluster 4: Southern P.* | ***Cluster 1 Core*** | *Cluster 2: Baltics* | *Cluster 3: Eastern P.* | *Cluster 4: Southern P.* | *Cluster 5: Lithuania* |
| Austria | **0.96** | 0.00 | 0.04 | **0.96** | 0.00 | 0.01 | 0.03 | **0.95** | 0.00 | 0.01 | 0.04 | 0.00 |
| Belgium | **0.97** | 0.00 | 0.03 | **0.67** | 0.00 | 0.01 | 0.31 | **0.62** | 0.00 | 0.01 | 0.37 | 0.00 |
| Bulgaria | 0.17 | 0.01 | **0.82** | 0.07 | 0.00 | **0.84** | 0.08 | 0.07 | 0.00 | **0.85** | 0.08 | 0.00 |
| Croatia | 0.41 | 0.02 | **0.57** | 0.28 | 0.01 | **0.46** | 0.25 | 0.29 | 0.01 | **0.41** | 0.27 | 0.03 |
| Czech Republic | 0.29 | 0.00 | **0.71** | 0.30 | 0.00 | 0.32 | **0.37** | 0.31 | 0.00 | 0.34 | **0.34** | 0.00 |
| Denmark | **0.95** | 0.00 | 0.05 | **0.91** | 0.00 | 0.01 | 0.07 | **0.90** | 0.00 | 0.01 | 0.08 | 0.00 |
| Estonia | 0.01 | **0.98** | 0.01 | 0.01 | **0.97** | 0.01 | 0.01 | 0.00 | **0.98** | 0.00 | 0.00 | 0.01 |
| Finland | **0.74** | 0.03 | 0.23 | **0.70** | 0.02 | 0.12 | 0.15 | **0.69** | 0.01 | 0.11 | 0.16 | 0.03 |
| France | **0.99** | 0.00 | 0.01 | **0.93** | 0.00 | 0.00 | 0.06 | **0.91** | 0.00 | 0.00 | 0.08 | 0.00 |
| Germany | **0.66** | 0.00 | 0.33 | **0.72** | 0.00 | 0.12 | 0.15 | **0.73** | 0.00 | 0.11 | 0.15 | 0.00 |
| Greece | 0.41 | 0.02 | **0.57** | 0.22 | 0.01 | 0.30 | **0.47** | 0.22 | 0.01 | 0.30 | **0.46** | 0.02 |
| Hungary | **0.91** | 0.00 | 0.09 | **0.76** | 0.00 | 0.04 | 0.20 | **0.74** | 0.00 | 0.03 | 0.22 | 0.00 |
| Ireland | 0.47 | 0.05 | **0.48** | 0.29 | 0.03 | 0.23 | **0.44** | 0.29 | 0.03 | 0.23 | 0.42 | 0.03 |
| Italy | **0.96** | 0.00 | 0.04 | **0.84** | 0.00 | 0.01 | 0.15 | **0.83** | 0.00 | 0.01 | 0.16 | 0.00 |
| Latvia | 0.00 | **0.99** | 0.00 | 0.00 | **0.99** | 0.00 | 0.00 | 0.00 | **0.96** | 0.00 | 0.00 | 0.03 |
| Lithuania | 0.04 | **0.92** | 0.04 | 0.04 | **0.87** | 0.06 | 0.03 | 0.00 | 0.00 | 0.00 | 0.00 | **1.00** |
| Netherlands | **0.93** | 0.00 | 0.07 | **0.77** | 0.00 | 0.02 | 0.21 | **0.75** | 0.00 | 0.02 | 0.23 | 0.00 |
| Norway | **0.80** | 0.00 | 0.19 | 0.44 | 0.00 | 0.08 | **0.47** | 0.41 | 0.00 | 0.08 | **0.51** | 0.00 |
| Poland | **0.86** | 0.00 | 0.14 | 0.35 | 0.00 | 0.04 | **0.61** | 0.32 | 0.00 | 0.04 | **0.64** | 0.00 |
| Portugal | **0.73** | 0.00 | 0.27 | 0.17 | 0.00 | 0.04 | **0.79** | 0.17 | 0.00 | 0.04 | **0.79** | 0.00 |
| Romania | 0.19 | 0.02 | **0.79** | 0.09 | 0.01 | **0.77** | 0.13 | 0.09 | 0.01 | **0.77** | 0.11 | 0.02 |
| Slovakia | 0.24 | 0.02 | **0.75** | 0.13 | 0.01 | **0.74** | 0.12 | 0.15 | 0.01 | **0.68** | 0.14 | 0.03 |
| Slovenia | 0.21 | 0.01 | **0.79** | 0.20 | 0.01 | **0.63** | 0.16 | 0.22 | 0.00 | **0.60** | 0.17 | 0.01 |
| Spain | **0.54** | 0.00 | 0.46 | 0.04 | 0.00 | 0.01 | **0.95** | 0.04 | 0.00 | 0.02 | **0.94** | 0.00 |
| Sweden | **0.87** | 0.00 | 0.12 | **0.77** | 0.00 | 0.04 | 0.19 | **0.77** | 0.00 | 0.04 | 0.19 | 0.00 |
| Switzerland | **0.90** | 0.00 | 0.10 | **0.71** | 0.00 | 0.04 | 0.24 | **0.69** | 0.00 | 0.04 | 0.27 | 0.00 |
| United Kingdom | **0.96** | 0.00 | 0.04 | **0.84** | 0.00 | 0.02 | 0.14 | **0.81** | 0.00 | 0.02 | 0.17 | 0.00 |
| United States | **0.94** | 0.00 | 0.05 | **0.76** | 0.00 | 0.02 | 0.21 | **0.73** | 0.00 | 0.02 | 0.24 | 0.00 |
| Japan | **0.77** | 0.00 | 0.22 | **0.60** | 0.00 | 0.10 | 0.30 | **0.59** | 0.00 | 0.09 | 0.31 | 0.00 |
| South Korea | 0.43 | 0.02 | **0.54** | 0.30 | 0.02 | 0.27 | **0.42** | 0.29 | 0.01 | 0.28 | **0.40** | 0.02 |
| | **Sample average silhouette** 0.4188 | | | **Sample average silhouette** 0.3088 | | | | **Sample average silhouette** 0.3100 | | | | |

Notes: The table summarizes the cluster results of our FCM approach of CF-filtered quarterly real GDP (1996 Q1–2015 Q4; m=1.5; c from 3 to 5) including the United States, Japan and South Korea. The values express relative membership of each cluster ($u_{ij}$). The highest cluster membership is signified by bold letters

**Table A3: Results for Hierarchical Clustering Using Weighted Average Linkage and the Euclidian Distance Norm (Whole Period 1996 Q1–2015 Q4)**




Notes: The dendrogram summarizes the cluster results of a weighted average linkage clustering approach based on the Euclidean distance norm and CF-filtered quarterly real GDP (1996 Q1–2015 Q4).

**Table A4: FCM Results based on the Manhattan Distance Norm (Whole Period 1996 Q1–2015 Q4)**

| | **3-Cluster Solution** | | | **4-Cluster Solution** | | | | **5 -Cluster Solution** | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| ***m=1.6*** ***CF Filtered Data*** | ***Cluster 1 Core*** | *Cluster 2: Baltics* | *Cluster 3: Eastern P.* | ***Cluster 1 Core*** | *Cluster 2: Baltics* | *Cluster 3: Eastern P.* | *Cluster 4: Southern P.* | ***Cluster 1 Core*** | *Cluster 2: Baltics* | *Cluster 3: Eastern P.* | *Cluster 4: Southern P.* | *Cluster 5: Romania* |
| Austria | **0.96** | 0.00 | 0.04 | **0.93** | 0.00 | 0.01 | 0.06 | **0.92** | 0.00 | 0.02 | 0.06 | 0.00 |
| Belgium | **0.95** | 0.00 | 0.05 | **0.65** | 0.00 | 0.02 | 0.33 | **0.65** | 0.00 | 0.04 | 0.31 | 0.00 |
| Bulgaria | 0.14 | 0.01 | **0.86** | 0.06 | 0.00 | **0.88** | 0.06 | 0.15 | 0.01 | **0.42** | 0.15 | 0.27 |
| Croatia | 0.31 | 0.02 | **0.67** | 0.30 | 0.02 | **0.46** | 0.23 | 0.06 | 0.00 | **0.87** | 0.05 | 0.02 |
| Czech Republic | **0.60** | 0.01 | 0.38 | 0.36 | 0.01 | 0.15 | **0.48** | 0.32 | 0.01 | 0.11 | **0.51** | 0.06 |
| Denmark | **0.93** | 0.00 | 0.06 | **0.85** | 0.00 | 0.02 | 0.12 | **0.85** | 0.00 | 0.03 | 0.11 | 0.00 |
| Estonia | 0.02 | **0.96** | 0.02 | 0.02 | **0.95** | 0.01 | 0.01 | 0.02 | **0.95** | 0.01 | 0.01 | 0.01 |
| Finland | **0.81** | 0.04 | 0.16 | **0.70** | 0.02 | 0.08 | 0.20 | **0.63** | 0.02 | 0.14 | 0.18 | 0.02 |
| France | **0.97** | 0.00 | 0.03 | **0.86** | 0.00 | 0.01 | 0.13 | **0.87** | 0.00 | 0.01 | 0.11 | 0.00 |
| Germany | **0.76** | 0.01 | 0.23 | **0.69** | 0.01 | 0.08 | 0.22 | **0.63** | 0.00 | 0.13 | 0.22 | 0.01 |
| Greece | 0.34 | 0.03 | **0.63** | 0.22 | 0.02 | 0.37 | **0.38** | 0.19 | 0.02 | **0.37** | 0.29 | 0.14 |
| Hungary | **0.91** | 0.00 | 0.08 | **0.77** | 0.00 | 0.03 | 0.20 | **0.75** | 0.00 | 0.06 | 0.19 | 0.01 |
| Ireland | **0.56** | 0.06 | 0.38 | 0.33 | 0.04 | 0.18 | **0.45** | 0.29 | 0.03 | 0.14 | **0.43** | 0.11 |
| Italy | **0.96** | 0.00 | 0.03 | **0.79** | 0.00 | 0.01 | 0.19 | **0.77** | 0.00 | 0.02 | 0.21 | 0.00 |
| Latvia | 0.01 | **0.98** | 0.01 | 0.01 | **0.97** | 0.01 | 0.01 | 0.01 | **0.97** | 0.01 | 0.01 | 0.00 |
| Lithuania | 0.07 | **0.83** | 0.10 | 0.09 | **0.73** | 0.11 | 0.07 | 0.09 | **0.61** | 0.18 | 0.07 | 0.06 |
| Netherlands | **0.95** | 0.00 | 0.05 | **0.76** | 0.00 | 0.02 | 0.22 | **0.73** | 0.00 | 0.02 | 0.24 | 0.00 |
| Norway | **0.76** | 0.01 | 0.23 | **0.49** | 0.01 | 0.11 | 0.40 | **0.46** | 0.01 | 0.16 | 0.34 | 0.03 |
| Poland | **0.82** | 0.01 | 0.17 | 0.38 | 0.00 | 0.05 | **0.57** | 0.37 | 0.00 | 0.08 | **0.53** | 0.01 |
| Portugal | **0.67** | 0.01 | 0.32 | 0.24 | 0.00 | 0.07 | **0.69** | 0.24 | 0.00 | 0.08 | **0.66** | 0.02 |
| Romania | 0.18 | 0.03 | **0.79** | 0.09 | 0.02 | **0.78** | 0.12 | 0.00 | 0.00 | 0.00 | 0.00 | **0.99** |
| Slovakia | 0.22 | 0.01 | **0.77** | 0.19 | 0.01 | **0.67** | 0.13 | 0.06 | 0.00 | **0.88** | 0.04 | 0.03 |
| Slovenia | 0.35 | 0.01 | **0.63** | 0.32 | 0.01 | **0.34** | 0.33 | 0.26 | 0.01 | **0.39** | 0.28 | 0.06 |
| Spain | **0.62** | 0.00 | 0.38 | 0.04 | 0.00 | 0.01 | **0.95** | 0.03 | 0.00 | 0.01 | **0.96** | 0.00 |
| Sweden | **0.90** | 0.01 | 0.09 | **0.73** | 0.01 | 0.04 | 0.23 | **0.70** | 0.00 | 0.06 | 0.23 | 0.01 |
| Switzerland | **0.86** | 0.00 | 0.14 | **0.63** | 0.00 | 0.06 | 0.31 | **0.63** | 0.00 | 0.06 | 0.30 | 0.01 |
| United Kingdom | **0.90** | 0.00 | 0.10 | **0.78** | 0.00 | 0.04 | 0.18 | **0.76** | 0.00 | 0.08 | 0.16 | 0.01 |
| | **Sample average silhouette** 0.4419 | | | **Sample average silhouette** 0.3088 | | | | **Sample average silhouette** 0.3470 | | | | |

Notes: The table summarizes the cluster results of our FCM approach of CF-filtered quarterly real GDP (1996 Q1–2015 Q4; m=1.6; c from 3 to 5) using the 'Manhattan distance.' The values express relative membership of each cluster ($u_{ij}$). The highest cluster membership is signified by bold letters.

**Table A5: Pre- and Post-Crisis FCM Results, Excluding 2008/2009 (Period 1: 1996 Q1–2007 Q4; Period 2: 2010 Q1–2015 Q4)**

| | **First Period (1996 Q1–2007 Q4)** | | | | **Second Period (2010 Q1–2015 Q4)** | | |
|---|---|---|---|---|---|---|---|
| ***m=1.7 (period 1) 1.9 (2) CF Filtered Data*** | Cluster 1: Core | Cluster 2: Baltics | Cluster 3: Eastern Periphery | Cluster 4: South Eastern Periphery | Cluster 1: Core | Cluster 2: Baltics | Cluster 3: Southern Periphery |
| Austria | **0.97** | 0.00 | 0.02 | 0.01 | **0.90** | 0.02 | 0.08 |
| Belgium | **0.88** | 0.00 | 0.07 | 0.05 | **0.84** | 0.01 | 0.16 |
| Bulgaria | 0.18 | 0.01 | **0.64** | 0.16 | **0.87** | 0.02 | 0.11 |
| Croatia | 0.06 | 0.01 | 0.03 | **0.90** | **0.88** | 0.02 | 0.10 |
| Czech Republic | 0.09 | 0.01 | **0.87** | 0.03 | 0.27 | 0.01 | **0.72** |
| Denmark | **0.84** | 0.01 | 0.10 | 0.04 | **0.92** | 0.01 | 0.07 |
| Estonia | 0.02 | **0.95** | 0.01 | 0.02 | 0.05 | **0.92** | 0.03 |
| Finland | **0.80** | 0.02 | 0.09 | 0.10 | **0.73** | 0.08 | 0.19 |
| France | **0.98** | 0.00 | 0.01 | 0.00 | **0.95** | 0.00 | 0.04 |
| Germany | **0.52** | 0.01 | 0.38 | 0.09 | **0.91** | 0.01 | 0.08 |
| Greece | 0.15 | 0.01 | 0.11 | **0.73** | 0.41 | 0.09 | **0.50** |
| Hungary | **0.89** | 0.01 | 0.06 | 0.05 | **0.67** | 0.02 | 0.31 |
| Ireland | 0.24 | 0.02 | **0.69** | 0.06 | 0.34 | 0.15 | **0.51** |
| Italy | **0.92** | 0.00 | 0.05 | 0.03 | **0.56** | 0.02 | 0.42 |
| Latvia | 0.01 | **0.96** | 0.01 | 0.01 | 0.05 | **0.92** | 0.03 |
| Lithuania | 0.18 | 0.26 | 0.13 | **0.43** | 0.06 | **0.91** | 0.03 |
| Netherlands | **0.94** | 0.00 | 0.05 | 0.01 | **0.87** | 0.01 | 0.12 |
| Norway | **0.79** | 0.01 | 0.09 | 0.11 | **0.76** | 0.04 | 0.19 |
| Poland | **0.75** | 0.01 | 0.13 | 0.11 | **0.64** | 0.01 | 0.34 |
| Portugal | **0.77** | 0.01 | 0.12 | 0.11 | 0.20 | 0.02 | **0.79** |
| Romania | 0.17 | 0.03 | **0.61** | 0.20 | **0.67** | 0.06 | 0.28 |
| Slovakia | 0.05 | 0.01 | 0.05 | **0.89** | **0.94** | 0.00 | 0.05 |
| Slovenia | 0.30 | 0.02 | **0.45** | 0.23 | **0.60** | 0.03 | 0.38 |
| Spain | **0.66** | 0.00 | 0.25 | 0.08 | 0.06 | 0.00 | **0.93** |
| Sweden | **0.87** | 0.01 | 0.08 | 0.04 | 0.46 | 0.03 | **0.51** |
| Switzerland | **0.88** | 0.00 | 0.09 | 0.03 | **0.83** | 0.02 | 0.15 |
| United Kingdom | **0.89** | 0.00 | 0.05 | 0.05 | **0.92** | 0.01 | 0.07 |
| | **Sample average silhouette** 0.5382 | | | | **Sample average silhouette** 0.5592 | | |

Notes: The table summarizes the cluster results of our FCM approach of CF-filtered quarterly real GDP for two separate time periods: 1996 Q1–2007 Q4 as the first and 2010 Q1–2015 Q4 as the second period. The values express relative membership of each cluster ($u_{ij}$). The highest cluster membership is signified by bold letters.