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Output gap similarities in Europe: Detecting country groups

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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, casting doubt on the endogeneity properties of the EA.

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

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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).[2] 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; 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 centre (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.

In previous studies authors such as Artis and Zhang (2002), König and Ohr (2013) and Wortmann and Stahl (2016) identify the core group through cluster analyzes based on different

[2] Within the theory of optimum currency areas (OCAs), 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 debated. 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.

sets of static macroeconomic criteria, among which cyclical similarities are only considered implicitly. 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), Lehwald (2013), Caporale et al. (2014), 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. 2014), but recent evidence suggests that it shows a great deal of business cycle synchronization with the core (Belke et al. 2016; Campos and Macchiarelli 2016). Moreover, while the literature has focused 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 'core' or '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 national supply and demand shocks with those of Germany as an 'anchor' or 'centre' 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) analyzes the synchronization between an aggregate EA (10) economic 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. Furthermore, Boreiko (2003), Kozluk (2005), Crowley (2008) and Quah (2014) employ cluster analyses of cyclical correlations between individual countries and Germany and/or the aggregate EA to assess the suitability of prospective EA member countries. As far as the period after the global financial crisis is concerned, Ferroni and Klaus (2015) conclude that Spanish cycle fluctuations have evolved asymmetrically to the other EA (core) countries of their study (Germany, France and Italy). Similar findings of Degiannakis et al. (2014) suggest that the core–periphery pattern has changed since the global financial crisis.

Obviously, an important assumption of such analyses is the choice of a suitable proxy for the supposed but unobservable European business cycle. So far, either Germany's business cycle or the EA's aggregate cycle are used frequently as such reference measures for business cycle synchronization analyses (see, for instance, Artis and Zhang 1997; Artis and Zhang 2001; Furceri and Karras 2008; Afonso and Sequeira 2010; Savva et al. 2010; Gächter et al. 2012; Mink et al. 2012, among others). 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 be assumed readily in advance, which casts doubt on many results of previous business cycle analyses.

Hence, there is a need to clarify empirically both the number of existing European business cycles and the countries belonging to them. In particular, the following questions emerge: (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?

The present paper addresses these questions simultaneously by employing a fuzzy clustering approach in 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 each country a degree of membership to the group-specific European business cycles at the centre 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. First, we offer a comprehensive classification of core and periphery countries independent from strict and arbitrary assumptions. All countries can be ranked according to their similarity to the computed centroid time series of the core cluster that serves as an appropriate reference for further analysis. The relative belongingness of each country to this European core business cycle may speak for or against EA membership. Second, we are able to investigate the relationship between the core and the peripheral European business cycles over time. This in turn provides relevant information for European policy makers aiming to achieve cyclical convergence within the EA.

Indeed, our analysis allows us to find answers to the three questions posed above. (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 a higher degree of 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 analysis and studies the relationship between the European core business cycle and the peripheral cycles. Moreover, the robustness of our findings is checked by assessing the impact of the ‘pre-crisis period’ and ‘post-crisis period’ in determining the overall core–periphery pattern. Finally, section 4 concludes.

2. Methodology

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 (EU-28 minus Cyprus, Malta and Luxembourg) plus Norway and Switzerland ranging from 1996Q1 to 2015Q4. 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. 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). 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 cyclical components from the time series using the band pass filter developed by Christiano and Fitzgerald (2003). The filter is set to extract periodic fluctuations lasting between 6 and 32 quarters. For robustness purposes, however, we also apply the commonly used high-pass filter by Hodrick and Prescott (1997), which does not change the general cluster solutions apart from some deviations in membership degrees (see the Appendix for the complete results). All the output gaps are then expressed as a percentage of the cyclical component of the trend component.

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 centre of the cluster. An iterative procedure varies the location of these centroids to minimize the weighted sum of the squared Euclidean distance between the objects and the centroids. In contrast to hard clustering, in which in each step of the process the data points exclusively belong to only one cluster, FCM assigns each object to all clusters by a set of weights. As these weights 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. Consequently, the coordinates of each centroid are calculated as 'c-means' of all data points according to the corresponding weight.

[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 on time series clustering. For further details, see Kaufman and Rousseeuw (2005).

In particular, the following objective function should be minimized:

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

where u is the fuzzy membership matrix indicating the weights of time series x_i in each cluster j and $\|x_i - v_j\|^2$ 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.[4] 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:

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

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

The algorithm then 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 cycles. Hence, a higher membership coefficient signifies greater proximity to the respective cluster's centroid, which allows a ranking of countries according to their degree of belongingness.

[4] 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. As our cluster analyses are based on quarterly time series data with a high degree of overlap, we achieve the highest silhouette at reasonable fuzziness by setting m to 1.5 for the whole sample period and to 1.7 for the subsamples.

However, the results of such a 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.[5] According to Nikhil and Bezdek (1995), the number of clusters to choose is generally between two and the square root of n. With just 27 countries in our sample, the illustration of all the cluster solutions thus allows us to trace 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*

b_i: *minimum average distance from the ith point to points in a 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

Business Cycle Clusters in Europe, 1996–2015

The results of our main cluster analysis are depicted in Table 1, which summarizes the membership coefficients of all 27 countries for different numbers of clusters c. A membership coefficient close to 1 indicates that the country is close to the centre 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 centred by those countries typically referred to as the European core countries.

[Table 1 about here]

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

This core cluster consists of the following 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 is a strong indication against using Germany's cycle as a proxy for the European core business cycle. Belgium, another country that might be expected to be near the centre 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.

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).[6] The high membership coefficients indicate that these countries form a very distinct cluster in which the centroid apparently lies 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.

According to the OCA literature, an ideal monetary union would consist of countries with synchronized business cycles. Hence, all the clusters that we identify would qualify as separate OCAs, since all the members of these clusters exhibit a high degree of business cycle similarity. 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

[6] 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.

inference on the costs of being a member of the EA. In this regard an adoption of the euro in the 'opt out' countries of Denmark, Sweden and the UK, as well the 'EU out' Switzerland, would be unproblematic. Surprisingly, the same holds for Hungary, the only CEEC that unambiguously is 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. 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.

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). In particular, we use the European core business cycle of the FCM analysis as a reference cycle for three time-varying synchronization measures.

[Figure 1 about here]

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.[7] Furthermore, 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 amplitude of the two business cycles.[8] Figure

[7] The correlation between time series g_i and reference series g_r is calculated at each point in time by the following formula: $\rho_{i,r}(t) = 1 - \frac{1}{2}\left(\frac{g_{i,t}-\bar{g}_i}{\sqrt{\frac{1}{T}\sum_{t=1}^{T}(g_{i,t}-\bar{g}_i)^2}} - \frac{g_{r,t}-\bar{g}_r}{\sqrt{\frac{1}{T}\sum_{t=1}^{T}(d_{r,t}-\bar{d}_r)^2}}\right)^2$. 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 on 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.

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

2 compares the three-year moving average of these measures for all four cluster centroids with the core time series as a reference. This allows us to draw several conclusions.

[Figure 2 about here]

First, the Baltics have a high correlation with the core time series (overall correlation coefficient of 0.88), which for most of the time period is around 0.9. 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. While the timing of up- and downswings of the core and Baltic business cycles coincide (indicated by high *synchronicity*), their amplitudes differ widely. 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.

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.

Third, the business cycle of the southern periphery exhibited 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.

Robustness Analysis: Core and Periphery before and after the Crisis

We cannot rule out the possibility that the overall grouping obtained by the FCM approach is driven by increasing divergences since the global financial crisis. Indeed, the 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 will 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 depict those solutions in Table 2, which result in the highest average silhouette at different values of *c*.

[Table 2 about here]

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 Romania), no such cluster is evident after the crisis at $c=3$. Instead, most countries of the former eastern periphery enter the core cluster indicating greater proximity than in the first period.[9] In the second period, the southern periphery cluster is formed around Portugal and Spain. 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 to the core in the first period. Conversely, in the second period, they belong to the southern periphery to a high degree (Belgium even switches membership).

[9] 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 completely integrated into the core cluster. All the cluster solutions are available upon request.

4. Conclusion

The recent euro crisis has underlined the need to address European business cycle patterns from a country group perspective. Previous research has often used 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 fuzzy clustering approach to assess empirically the core–periphery pattern 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 are able to detect all the group-specific 'European business cycles' apparent in the data: we identify a core group opposed to several clusters on the Eastern and Southern European periphery. Furthermore, our approach yields a time series of the European core business cycle, which is superior to other previously used reference cycles, such as supposed anchor countries' business cycle or the EA aggregate, and could be employed in future research on European business cycles.

Since we can quantify each country's degree of belongingness to the corresponding group-specific business cycles, our analysis provides useful information about the readiness of individual countries to join the EA with regard to their cyclical similarities with the core. 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 countries on the eastern or southern periphery. However, while some non-EA members clearly belong to the core, several peripheral countries with less synchronized cycles have adopted the euro, instead. If the EA persists in its current composition, a common monetary policy and exchange rate is thus likely to remain costly for several members. Conversely, our results show that there are country groups in Europe qualifying as separate OCAs in terms of business cycle similarities.

Ultimately, our findings reveal that the relationship of the eastern and southern periphery with the core has changed since the global financial crisis. This casts doubt on the 'endogeneity hypothesis' by Frankel and Rose (1997), since the divergence of the southern periphery shows that business cycle synchronization may decrease despite countries sharing a common currency. By contrast, the convergence of the eastern periphery suggests that under certain conditions – among them not necessarily a common currency – business cycle synchronization can indeed increase. Obviously, the driving forces behind these developments are of great interest to scholars and policy makers alike and should be a topic for future research.

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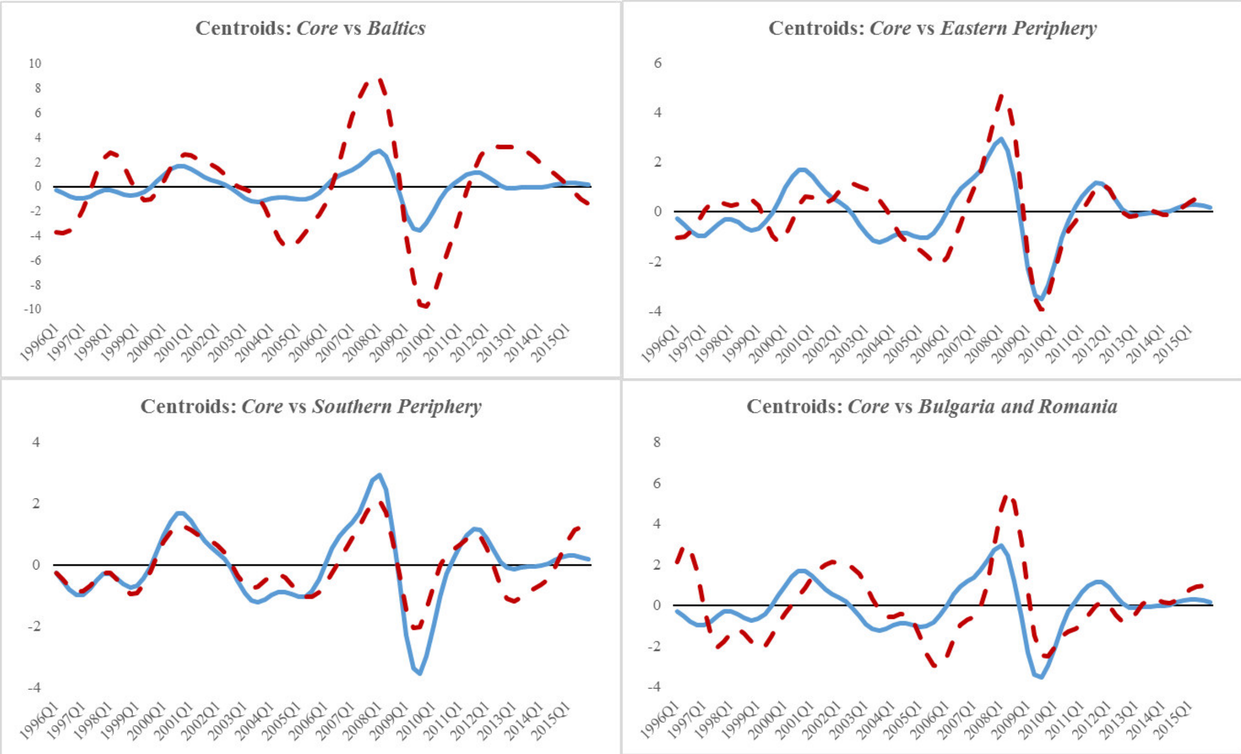
Tables and Figures

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 3 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				

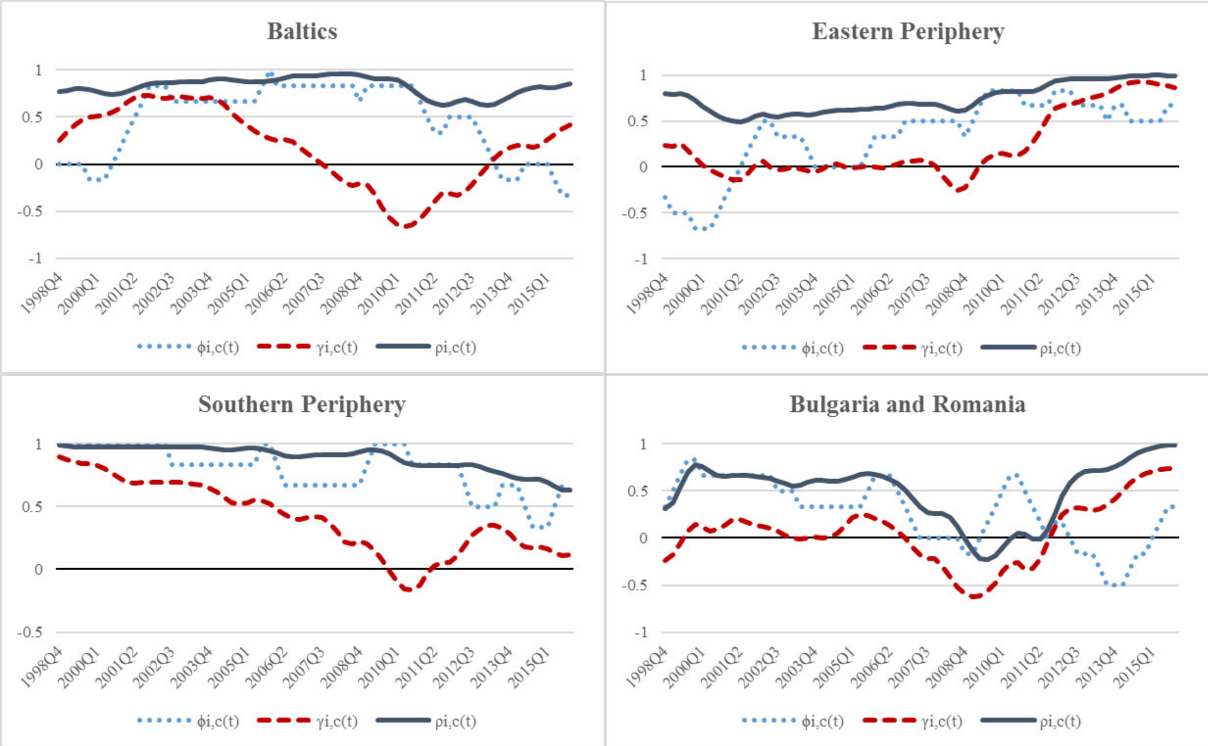
Notes: The table summarizes the cluster results of our FCM approach of CF filtered quarterly real GDP (1996 Q1–2015 Q4; m=1.5; c from 3 to 5). The values express relative membership of each cluster (u_{ij}). The highest cluster membership is signified by bold letters.

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 1996Q1–2015Q4.

Figure 2: Relation of 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 by 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.

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: 1996Q1–2007Q4 as the first and 2008Q1–2015Q4 as the second period. The values again express relative membership of each cluster (u_{ij}). The highest cluster membership is signified by bold letters.

Appendix

Table A1: FCM Results, 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 (1996Q1–2015Q4; 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.