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Synchronization and diversity in business cycles: a network analysis of the European Union

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ABSTRACT

In this article, we use a correlation matrix and its internal networks to analyse business cycle synchronization across Europe since 2000. This methodology allows us to summarize individual country interactions and co-movements while also capturing the existing heterogeneity of connectivity within the European economic system. Our results indicate that synchronization of the euro zone countries remained stable from 1999 until the current financial crisis, after which co-movements increased sharply and synchronization rose to the highest in the time sample. By endogenously identifying clusters of countries with close connections in their business cycle, we also refute the commonly accepted notion of identifiable core and peripheral euro zone countries.

KEYWORDS

Business cycle synchronization; European countries; euro zone; complex systems; network topology; minimum spanning tree

JEL CLASSIFICATION

E32; C45; F45

I. Introduction and related literature

Since the outbreak of the global financial crisis, the costs and benefits of maintaining the European Monetary Union (EMU or euro zone) have moved to the forefront of academic and policy debate (see Lane 2012 for a useful overview). The rapid spread of the 2010 Greek crises to other peripheral EMU countries, particularly, underscores the economic and political challenges faced by a currency union of many heterogeneous countries. It is also worth noting that although the 2008 financial crisis was the actual starting point of the European economic crisis, the prosperous international financial environment of 1999–2007 enabled the accumulation of macroeconomic, fiscal and financial vulnerabilities without any apparent effect on the prevailing good performance (Wyplosz 2006; Caruana and Adjiev 2012). Admittedly, at the time of writing, the euro zone seems to be recovering in terms of both finances and debt market stabilization; however, the Syriza victory in Greece's January 2015 elections clearly challenged the austerity policy imposed on that country, making its default and departure from the EMU again seem plausible.

It is also significant that the economic situation during the long economic crisis has been far from homogenous among EMU members. Whereas Greece, Portugal, Ireland, Spain, Italy and to some extent even France and the Netherlands have suffered financial turbulence and tensions due to the refinancing of public and private debt, other EMU countries, especially Germany, have easily obtained funds to finance their economies. This unbalanced economic situation inside the euro zone is to some extent related to the common monetary policy before and after the beginning of the 2008 global crisis, which have differing effects on each EMU member's economy because of different business cycle dynamics. Giving up the euro might thus appear an option for either single countries or groups of countries, not only to guarantee survival of the monetary union but also to achieve their own economic growth.

The costs and benefits of a currency union are closely related to the theory of optimum currency

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areas (OCAs) first introduced by Mundell (1961). Giving up their own currencies and joining the euro zone implies that these countries[1] have voluntarily relinquished control over their monetary and exchange rate policies. Thus, the effectiveness of a monetary policy and the benefits of the currency union depend on the extent to which member countries share certain common characteristics, the so-called OCA properties. Among these properties, the similarity of economic cycles is extremely important if a common monetary policy is to be optimal for all union members (e.g. Artis and Zhang 1999; De Grauwe and Mongelli 2005; Mongelli 2008).[2] The lower the business cycle integration among EMU countries, the greater the likelihood of asymmetric shocks, which can induce severe losses to members that have relinquished their own exchange and monetary policies. In addition, as evidenced by the contagion of the Greek crisis, such shocks may spread to the remaining union countries.

The literature on business cycle synchronization in the euro zone links this phenomenon to three main issues: the factors driving business co-movement, business cycle similarities (including whether a uniform European business cycle really exists) and the heterogeneity induced by synchronization between several diverse countries. Researchers investigating the first examine many aspects, including whether the increasing economic liaisons (especially trade) that should arise from EMU membership result in tighter synchronization (Frankel and Rose 1998; Baxter and Kouparitsas 2005; Artis and Okubo 2011). Other studies emphasize the role of fiscal policies (Crespo Cuaresma and Fernández-Amador, 2010) or institutional settings and market regulations (De Grauwe 2005). Such research, however, offers no consensus on which determinants of business cycle synchronization are the most important (Baxter and Kouparitsas 2005).

Investigation into whether business cycles have become more similar since the 1999 launch of the euro include Massman and Mitchel's (2004) historical overview, which identifies periods of convergence and divergence between 12 euro zone countries over the last 40 years. Most studies in this area, however, report an increase in business cycle synchronization for most European and Eastern European countries (Rose 2008; Darvas and Szapáry 2008; Saava et al. 2010). The extensive analysis by Darvas and Szapáry (2008), for example, points to a higher degree of synchronization in the core euro zone countries of Germany, Austria, France, Belgium, Italy and the Netherlands but less among peripheral members like Finland, Ireland, Portugal and Spain. It also indicates that Hungary, Poland and Slovenia have achieved a higher degree of synchronization, whereas the Czech Republic and Slovakia are less synchronized, and the Baltic States are apparently not synchronized at all. Weyerstrass et al. (2011) also fail to confirm that euro zone countries have become more synchronized since 1999.

As to the question of whether a European business cycle truly exists, Kose, Otrok, and Whiteman (2003), Artis (2003), Massman and Mitchel (2004), Camacho, Perez-Quiros, and Saiz (2006) and Lehwald (2013) argue that identifying a single European business cycle is difficult because only a small part of euro zone output can be attributed to a common European factor. Nevertheless, Artis, Krolzig, and Toro (2004) by using a Markov-switching vector autoregression model provide evidence for the existence of such a common cycle in nine European countries from 1970 to 1995 based on an index of industrial production and gross domestic product (GDP). More recent studies, in contrast, focus on the effects of the global financial crisis on European business cycle synchronization, which Gächter, Riedl, and Ritzberger-Grünwald (2012) report has decreased markedly since 2007 in both dispersion and the correlation between output and industrial production for all euro zone countries. Matesanz, Ortega, and Torgler (2013), however, demonstrate a sharp increase in output co-movements since 2008, not only for European countries but also for most developed and some developing countries.

[1]The European Monetary Union currently comprises 19 countries: of these, Austria, Belgium, France, Finland, Germany, Ireland, Italy, Luxembourg, Netherlands, Portugal and Spain have been part of the euro zone since 1999; Greece joined in 2001, Slovenia in 2007, Cyprus and Malta in 2008, Slovakia in 2009, Estonia in 2011, Latvia in 2014 and Lithuania in 2015.

[2]The optimum currency area (OCA) literature particularly emphasizes a common budget and fiscal policy (Kenen 1969), as well as the integration of such production factors as job markets (Mundell 1961), as important characteristics for reducing the effects of asymmetric shocks in the currency areas. These two features, however, seem politically difficult to achieve in the EU even during the current European fiscal and debt crisis (for extensive reviews of OCA theory, see De Grauwe 2005; and Mongelli 2008)

A third and recent strand of literature employs a broad spectrum of methodologies to identify the heterogeneity and complexity induced by business cycle synchronization among large groups of countries. Aguiar-Conraria and Soares (2009), for instance, use wavelet analysis to differentiate more synchronized countries (Germany, France, Austria, Spain and the Benelux) from less synchronized countries (Portugal, Italy, Greece and Finland), showing also that except for Portugal, these less synchronized countries are converging to the euro zone core. Gómez, Ortega, and Torgler (2012) then use complexity and clustering analysis to identify different European business cycle synchronization paths. Caraiani and Ben-Jacob (2013) analyse business cycle synchronicity and causality using 1970–2009 data for two different country samples (G7 and OECD) to show an intense link between Southern European countries and the world business cycle. Finally, Papadimitriou, Gogas, and Sarantitis (2015) apply a minimum dominating set specified by a determined threshold-minimum dominating set (T-MDS) to networks of output GDP in 22 European countries between 1986 and 2011 to provide evidence for increased output synchronization in the post-euro era between all countries, but especially EMU members.

It should be emphasized, however, that studies related to this issue are extensive and heterogeneous, analysing a diverse and to some extent controversial[3] range of main objectives, employing a broad range of methodologies, using a variety of data sets and drawing very different conclusions. This study therefore focuses on describing the network topology, hierarchy and evolution of business cycle synchronization across Europe in recent years. To do so, we examine GDP and co-movements in 16 EMU member countries (EM) and synchronization across four Eastern European non-EMU member countries (EEN), three old European non-EMU members (OEN)[4] and all countries in these three samples. In contrast to previous studies, we characterize business cycle synchronization by building a correlation matrix based on how closely countries' output growth-related elements are related and then constructing within-matrix networks. This methodology, first used to analyse topology and hierarchy in financial markets (Mantegna 1999; Ortega and Matesanz 2006), has now been extended to the analysis of business cycle synchronization (Miskiewicz and Ausloos, 2010; Matesanz, Ortega, and Torgler 2013) and growth convergence (Brida et al. 2011).

This matrix and network analysis, by capturing the presence of co-movement heterogeneity and diversity between all countries analysed, offers new insights into country interdependence and interactions, thereby contributing to the existing literature in several ways. First, it provides a simple description of synchronization dynamics within the real output of European countries, endogenously revealing the heterogeneity and complexity of output connections for each country. Second, by exploiting the information in the correlation matrix, as well as its internal networks, it outlines the evolution of the topological configuration of countries' co-movement over the business cycle, so clarifying the regionalization of European correlations in output growth and further explaining macroeconomic dynamics.

The analysis yields several important findings: First, the output synchronization of EM countries remained relatively stable from 1995 until 2007/2008 but has increased sharply during the current financial crisis. After 2008, however, the economic performance of both EM and EEN countries shows increasing heterogeneity, indicating a desynchronization process. The synchronicity dynamics are also linked to a period of in-phase co-movement, suggesting spillover effects from one country to another. Second, our results give little indication of the commonly accepted divide between core (usually Germany, Austria, Netherlands and France) and so-called PIIGS periphery countries (Portugal, Ireland, Italy, Greece and Spain). For instance, over the entire period, Italy, France, Germany, Austria and Spain enjoy similar business cycle synchronism. In fact, when we use rolling windows to characterize co-movement evolution, Italy, France and Spain appear more connected than, for instance, Germany, Austria or the UK. Countries like Greece, Portugal and Poland even appear to negatively affect the euro zone's stability and cohesion.

[3]De Haan, Inklaar, and Jong-A-Pin (2008) provide an excellent overview of the issue including results, data sets, methodologies and strategies for measuring business cycle synchronization. Also valuable are Fidrmuc and Korhonen's (2006) meta-analysis of 35 previous studies and Gächter et al.'s (2012) review of recent studies and their results.

[4]The old European non-EMU member group includes Sweden, the UK and Denmark (see the Appendix for a complete country list).

The rest of the article is organized as follows. Section II describes the data set and numerical methods, after which Section III reports the main findings and compares them with previous and methodologically different works. Section IV summarizes the findings and offers some concluding remarks.

II. Data and methodology

Data

The data set, downloaded from Eurostat, consists of real quarterly GDP figures for 23 countries over the 1995Q1–2015Q3 period, which encompasses the entire euro period from preparation to launch of the common currency through both the global and European financial crises. Because our intent is to address topological and hierarchical structure and evolution based on the degree of synchronization between countries' economies, we employ only global output data as our measure of the business cycle. Other variables, such as industrial production and exports, are tradable and so do not fully capture general economic performance. Conversely, more specifically domestic variables like consumption or services do not respond to certain international synchronization linkages.

One widely used method for stabilizing or removing trends in the long-run growth path of a GDP is the Hodrick-Prescott (1997) filter, which we use to exclude trends and enable network calculations based solely on the countries' business cycles. Given our interest in monetary policy efficiency for any given currency area, these cycles are the most important component of the raw data. In Supplementary Figures 1 and 2, we report the time series corresponding to the GDP and GDP cycles, respectively, for each country, although in the remainder of the article, we use only the cyclical component (*GDPc*) of the Hodrick–Prescott decomposition for our analysis.

Numerical methods

Hierarchical analysis

To quantify interaction and synchronization between two or more time series, we use both the cross-correlation coefficient ρρand the Kendall rank correlation, τ. Given two time series $\mathbf{x}_i = x_i(k), k = 1, N_{win}$ and $\mathbf{x}_j = x_j(k), k = 1, N_{win}$, the cross-correlation coefficient between *GDPc* of country *i* and *GDPc* of country *j* in a time window of N_{win} values is

$$\rho_{ij} = \frac{\sum_{k=1}^{N_{win}} (x_i(k) - \overline{x_i})(x_j(k) - \overline{x_j})}{\sqrt{\sum_{k=1}^{N_{win}} (x_i(k) - \overline{x_i})^2 \sum_{k=1}^{N_{win}} (x_j(k) - \overline{x_j})^2}} \quad (1)$$

where $\bar{x}_i = 1/N_{win} \sum_{k=1}^{N_{win}} x_i(k)$. Similarly, the Kendall τ rank correlation between *GDPc i* and *GDPc j*, τ_{ij} in a time window of N_{dat} is

$$\tau_{ij} = \frac{C - D}{N} \quad (2)$$

where C is the number of *concordant* pairs, meaning that for the same k, both $x_i(k) > x_j(k)$ and $y_i(k) > y_j(k)$ or $x_i(k) < x_j(k)$ and $y_i(k) < y_j(k)$. D is the number of *discordant* pairs, meaning that for the same k, $x_i(k) > x_j(k)$ and $y_i(k) < y_j(k)$ or $x_i(k) < x_j(k)$ and $y_i(k) > y_j(k)$. T is the number of *tied* pairs of data points that occur when one or both variables remain constant, and $N = C + D + T$ is the total number of data points in the time series. Because the Kendall correlation generally measures the proportion of concordant pairs minus the proportion of discordant pairs over the total number of pairs, Kendall's $\tau\rho$ better describes the association between two variables than do traditional linear correlation coefficients. Here, Kendall's τ is $-1 < \tau < 1$.

In our particular case, $\mathbf{x}_i = x_i(k), k = 1, N_{dat}$ corresponds to each of the $GDPc_i(k)$ time series so that $1 \leq i \leq 23$ (number of countries) and $1 \leq k \leq N_{dat}$(number of quarters analysed). To transform correlations ρ_{ij} *or* $\tau_{i,j}$ into distances, we follow Gower (1966) and define the distance *d(i,j)* between the evolution of two time series x_i and x_j as

$$d(i,j) = \sqrt{\vartheta_{ii} + \vartheta_{jj} - 2\vartheta_{ij}} = \sqrt{2(1 - \vartheta_{ij})} \quad (3)$$

where $\theta_{i,j}$ is the absolute value of the Pearson or Kendall coefficient. We then use the nodes (countries) and corresponding links (distances) among them, to construct a hierarchical tree and interactions network. More specifically, using the Kruskal (1956) algorithm, we first construct a minimum spanning tree (MST), a simple loop-free graph that displays the most important links and communities in the network, and then calculate the cost of the

MST by summing all the links among all the MST nodes. This MST cost sheds light on the degree of correlation (synchronization) among the whole set of elements in the network: the lower the cost, the less the distance between MST members and thus the tighter the links among them.

It is also possible to construct a hierarchical data tree (HT) by using the single-linkage clustering algorithm (Johnson 1967) to cluster data into groups of members that demonstrate tight connections. In fact, such clustering is the usual way to define *communities* (Wasserman and Faust 1994) in a complex network, in which each member of a particular community shares some characteristics with other members of the same community.

The Pearson correlation (Equation 1) and its corresponding distance (Equation 3) will be used throughout the present article. The equivalent figures based on the Kendall correlation (Equation 2) and the Kendall-based distance (Equation 3) are presented as Supplementary material.

Network analysis and group cohesion

We also perform network analysis for each temporal window by constructing networks based on the absolute values of the correlation matrices elements, either Pearson or Kendall, using only statistically significant (p-value < 0.05) correlations as network links. Based on our country samples, we build three subnetworks, EM, OEN and EEN, and then calculate the cohesion (White and Harary 2001) for each case. This measure evaluates the level of connectedness in a graph, quantified by the minimum number of edges needed for removal from the graph in order to obtain a network that is not strongly connected. We thus use it to evaluate whether certain countries contribute to making the euro zone network (EM group) more robust.

Lead/lag relations between GDPc time series

For lead/lag relations, the important question is whether a low Pearson correlation value always implies uncoupled behaviour between two different *GDPc* time series. We assume not because if two time series were highly correlated but shifted in time with respect to each other, they would have a low zero-lag correlation but high-time-shifted correlation. This outcome would imply that one is leading/lagging the other. To address this issue, we implement two different calculations, one for correlation and the other for Granger causality. In the first, we evaluate correlation values for the case of a temporally shifted time series up to two temporal windows (2 years) and then select the maximum (absolute) value of the correlation in that window. This procedure provides five correlation values: $\Delta t = -2, -1, 0, 1$, or 2, with $\Delta t = 0$ corresponding to 'usually employed'. We use both these correlations, $\Delta t = 0$ and the correlation maximum in the [−2,2] interval, in our later analyses. We next calculate Granger causality to identify potential causality mechanisms and eliminate spurious lead/lag relations using Wiener's (1956) test for a causal relation between two time series in the context of linear auto-regressive models. First, given two time series $\mathbf{x} = x_k, k = 1, N_{dat}$ and$\mathbf{y} = y_k, k = 1, N_{dat}$, we use Granger causality (Granger, 1969) to determine whether future values of $\mathbf{x}$ are better predicted by using past values of $\mathbf{y}$ instead of past values of $\mathbf{x}$ exclusively. If so, $\mathbf{y}$ Granger causes $\mathbf{x}$. We then fit a linear auto-regressive model of order L to each time series $\mathbf{x}$ and $\mathbf{y}$, with its corresponding parameters a_i (in $\mathbf{x}$) and b_i (in $\mathbf{y}$) and SEs ε_x and ε_y, such that

$$\begin{aligned} x_k &= \sum_{i=1}^{L} a_i\, x_{k-i} + \varepsilon_x \\ x_k &= \sum_{i=1}^{L} a_i\, x_{k-i} + \varepsilon_x + \sum_{i=1}^{L} b_i\, y_{k-i} + \varepsilon_y \end{aligned} \tag{4}$$

If the second prediction *is better* than the first, then past values of $\mathbf{y}$ influence present values of $\mathbf{x}$. We quantify 'better' in a statistical sense by comparing ε_x and $\varepsilon_y\rho$ as follows:

$$GC_{y\to x} = \ln \frac{\mathrm{var}(\varepsilon_x)}{\mathrm{var}(\varepsilon_y)} \tag{5}$$

such that $GC_{y\to x}$ is nonnegative and the greater $GC_{y\to x}$ the better the fit of the combined model, implying a causality from $\mathbf{y}$ to $\mathbf{x}$. The statistical significance of this equation can then be assessed using the Fisher test:

$$F = \frac{\frac{RSS_x - RSS_y}{L}}{\frac{RSS_y}{N_{dat} - 2L - 1}} \tag{6}$$

where RSS_x and RSS_y are residual sums of the squares of models $\mathbf{x}$ and $\mathbf{y}$, respectively. In our case, time series $\mathbf{x}$ and $\mathbf{y}$ are both replaced by the *GDPc* (Equation 1) for two different countries i and *j*, and the *F*-statistic is evaluated with statistical significance set to 5%.

Time window analysis

To examine the temporal behaviour of output co-movement, we also calculate distance correlation matrices for overlapping windows of 3 years (12 quarters) forward in time, which we move over the entire sample period in quarterly increments beginning in 1995Q1. In addition to gradually uncovering changes in correlation – and thus the causality of any other calculations – this procedure smooths changes and permits a clearer visualization of the time at which they occur. Because there is a trade-off between temporal resolution and statistical confidence, the election of 12 quarters seems to fit both criteria. Whereas short temporal windows tend to be strongly affected by temporal circumstances and can potentially yield misleading results, longer windows provide a longer-term view, reflecting more permanent structural economic characteristics.[5] Hence, to enable comparison among different groups of unequal numbers of countries, we sum matrix distance coefficients for each window and normalize them to country number to produce a distance average between all countries in the group. Each data set thus represents the sum of metric distances among all countries in the past time window. We also calculate the corresponding MSTs in each time window and derive MST cost by summing all the metric distances represented in each tree branch. As in our previous calculations, we normalize the sum of branch distances to the number of countries, thereby allowing comparison between different country groups. In this case, we obtain the average of the minimum distances.

The sum of matrix distances represents the level of interdependence among all countries, a synchronization measure we label *global distance. MST cost* represents the interdependence of the closest connections in the business cycle for each country. In the case of global distance, the lower the value of the normalized distance coefficients, the tighter the coupling inferred among all countries. In the same way, the lower the value of the sum of distances represented in MST cost, the tighter the co-movement of the first distances among countries.

III. Empirical results

Cross-country hierarchical structure

Figure 1, which outlines the MST in our group of countries across the entire sample based on distance, gives a rough impression of the topological organization of business cycle synchronization. Figure 2 illustrates the HT for the same group of countries, with the hierarchical tree cut at certain levels to better reveal the clustering structure. Whereas Figure 1 only indicates which countries are more connected and which seem to have a specific output cycle, the dendrogram in Figure 2 permits analysis of the hierarchy based on proximity in the GDP dynamics. In fact, by explicitly demonstrating the intensity of co-movements, this figure identifies both groups of countries with similar business cycle dynamics and single countries with more isolated economic growth paths.

These two figures do in fact suggest the existence of at least two different European business cycle synchronization groups, as suggested by Camacho, Perez-Quiros, and Saiz (2008) and Aguiar-Conraria and Soares (2009). One large cluster consists of the mostly Western European countries of Austria, Belgium, France, the Netherlands, Germany, Italy, Spain, Finland, Denmark, Slovenia and even Sweden (a non-euro country), while the other encompasses the Eastern European countries of Estonia, Latvia, Lithuania and Hungary, together with the UK. We also observe a third cluster made up of Luxemburg, Greece, Portugal, Poland, Cyprus and Romania, all of whom exhibit more isolated country-specific economic growth dynamics than nations in the other groups. In terms of connectivity, the greatest amount of coupling is evident in Germany, Austria and France and the least in Luxemburg, Slovakia and Greece. This MST and HT analysis thus constitutes a structural approach to assessing business cycle synchronization, one capable of profiling output growth connections across an entire set of country samples. Nevertheless, because business cycle synchronization evolves as economic, institutional and policy liaisons change over time, we further investigate the evolution of co-movements in individual countries using a time window analysis.

[5]Using 2- and 5-year windows yields similar results (outcomes available from the authors upon request).

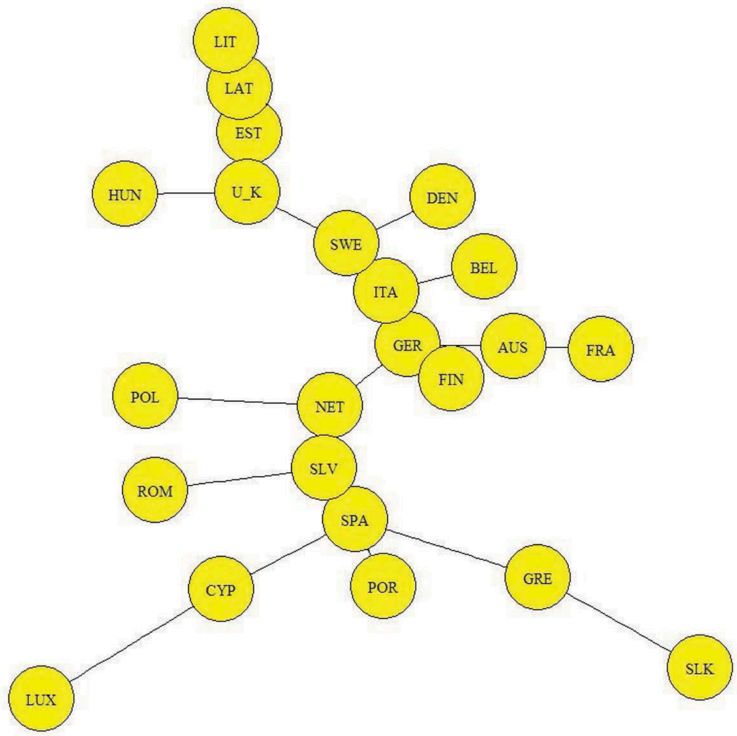

Figure 1. Pearson-based minimum spanning tree (MST): GDP cyclical component; 1995Q1-2015Q3; 23 countries.

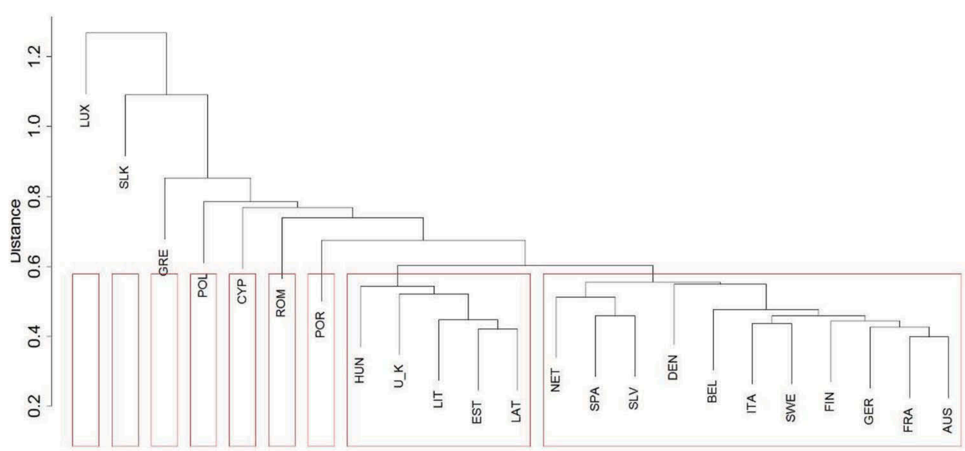

Figure 2. Pearson-based Hierarchical Tree (HT), GDP cyclical component, 1995Q1-2015Q3, 23 countries.

Time window analysis

Because the aim of the time window analysis is to describe the evolution of business cycle synchronization, Figure 3 plots the MST cost for EM, EEN and OEN countries in 3-year overlapping windows.[6] Each data point represents the sum of the MST branches in each temporal window, thereby describing the co-movements inside each group. For most groups, internal synchronization remains stable prior to the 2008 global financial crisis, although interestingly, the OEN group (UK, Sweden and Denmark), which is outside the euro zone, shows the strongest output synchronization. This is also the only group to show an increase

[6]Although the results for *global distance* (the sum of all coefficients in the correlation matrix) are not graphed because of space constraints, they are qualitatively similar to those for *MST cost*. The global distance figure is available from the authors upon request.

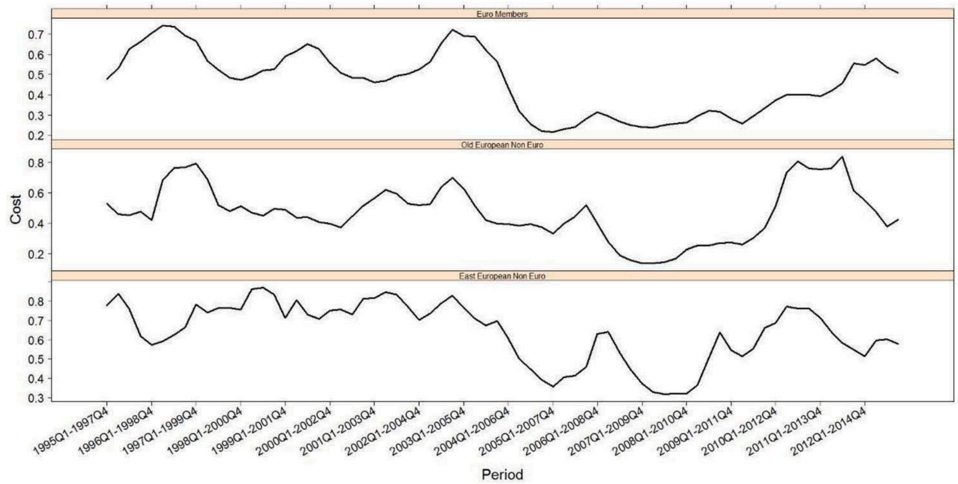

Figure 3. Pearson-based normalized MST cost: 3-year overlapping windows; selected regions.

in co-movement before 2007/2008. Overall, the intense increase in economic cycle synchronization triggered globally by the financial crisis, especially in developed countries, remains high until approximately 2010. The EM group, particularly, exhibits a longer period of high co-movement, which decreases only at the end of the analytic period.

As the financial crisis evolves, synchronization decreases for all groups, suggesting that countries within the Euro zone and eastern non-euro countries are experiencing heterogeneity in their paths of economic recovery.[7] We can therefore infer that the output co-movements of these sub-systems have remained stable during the life of the euro. Nevertheless, as the global financial crises develop, synchronization decreases because of differing responses in foreign and domestic economic policies. Such divergent evolution of output paths indicates pronounced desynchronization during the crisis period, as also identified by Gächter, Riedl, and Ritzberger-Grünwald (2012) and Lehwald (2013).

To analyse how the dynamics of every country's business cycle affect overall synchronicity in the euro zone, we first calculate the cohesion coefficients for the entire EM group and the EM group with one country removed and then deduct both coefficients to isolate the effects of every single country over the whole group minus one country. We then calculate the cohesion coefficient for the EM group and separate cohesion coefficients for the remaining countries and then again deduct both coefficients to identify the effects of a country joining the euro zone (see Figures 4–6). For the EM group, whereas removing one country from the group has no significant effect on group cohesion, removing Greece and Portugal during the financial crisis period improves cohesion, implying that these countries negatively affect synchronization cohesion inside the euro zone. Admittedly, Cyprus, Slovenia, Slovakia, Estonia and Luxemburg also demonstrate negative effects on European cohesion, but except for Luxemburg, these countries were not part of the euro zone at the time. With regard to the other two groups, no negative effects are evident from Hungary and Romania, or to a lesser extent from Denmark and Latvia. Overall, therefore, the cohesion analysis demonstrates that the overall efficiency of the common monetary policy is indeed negatively affected by the business cycle synchronicity of certain countries, in particular, Greece and Portugal, the two nations most affected by the financial and debt crisis.

Country dynamic importance in the network

Finally, we use an overlapping windows analysis to assess how important each country has been to the network over time. We measure this importance in two ways. First, we present the evolution of the number of connections (NCs) or connectivity of each country across the MST network. This simple

[7]Some Southern European countries (Greece, Ireland, Portugal and Spain) have suffered protracted stagnation in their economic performance over the last two years, while Germany, France and the Netherlands (among others) have been performing much better in aggregate terms.

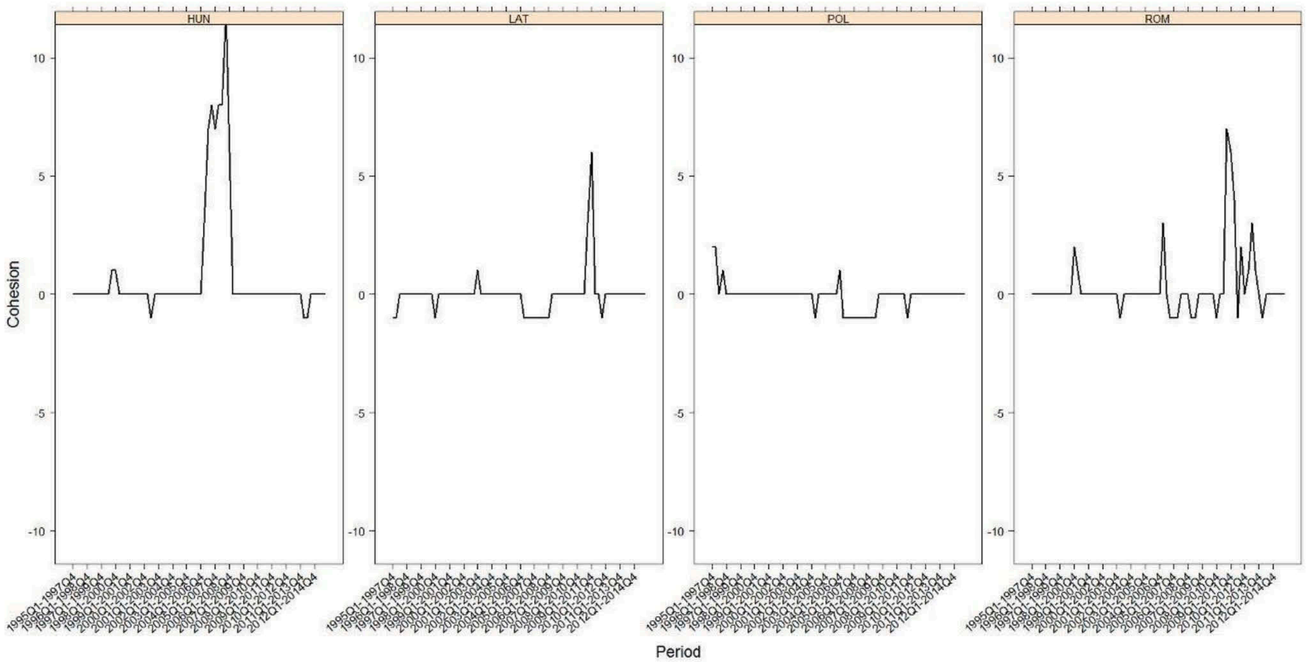

Figure 4. Cohesion: 3-year overlapping windows; 1995Q1–2015Q3; four East European non-euro countries; EEN. Pearson correlations are used.

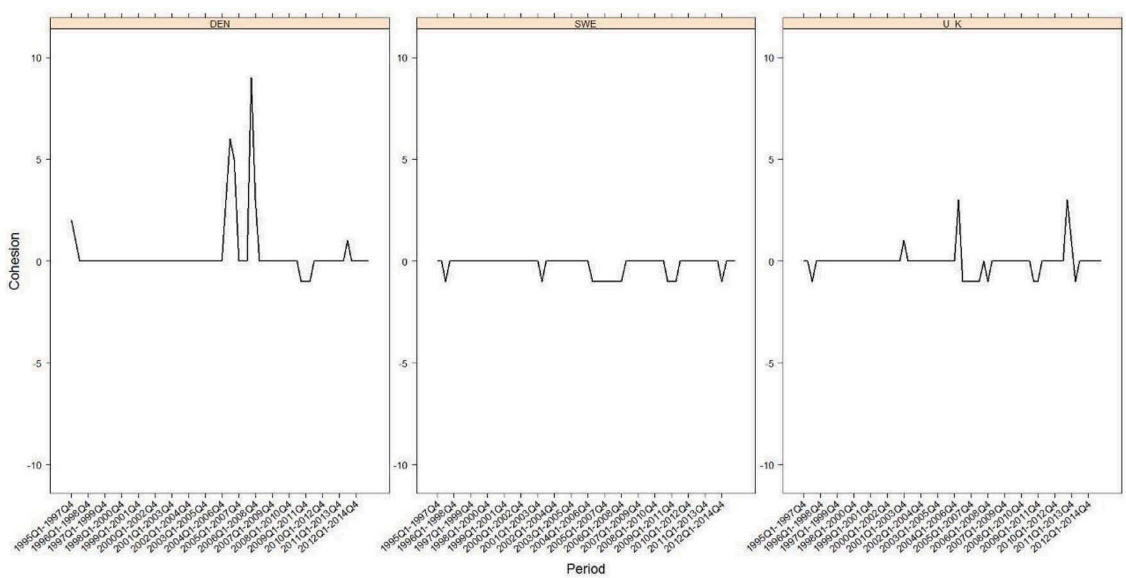

Figure 5. Cohesion: 3-year overlapping windows; 1995Q1–2015Q3; three old European non-euro countries; OEN. Pearson correlations are used.

measure indicates the importance of every country in the network in terms of connectivity to the others (see Figure 7). Very coloured square represents the previous 3 years' NC and IC inside the MST for each country; white or grey indicates little NC or IC, while black colours indicate high NC or IC. Second, in Figure 8, we also demonstrate the significant variation in connectivity over time, with France, Spain and to some extent Germany increasing the number of their connections around the 2008 crisis. This figure also shows that of the larger European countries, France, Spain and Italy are the most connected globally, while Germany and the UK are much less connected. After the

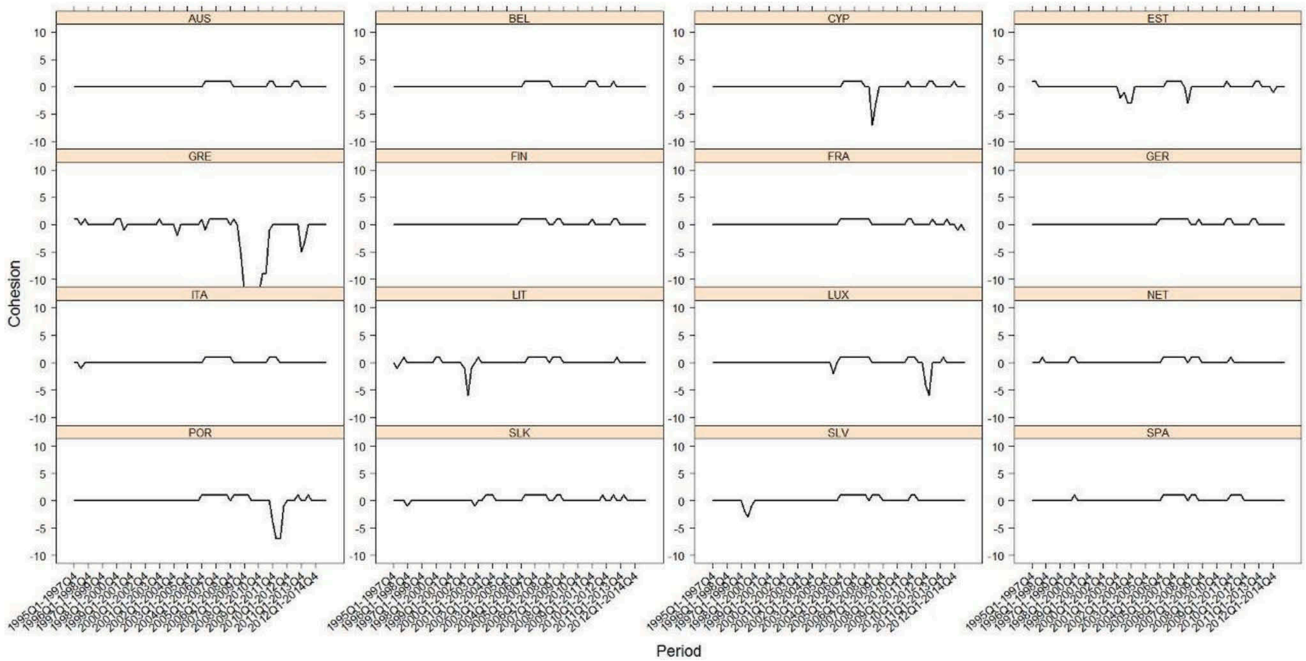

Figure 6. Cohesion: 3-year overlapping windows; 1995Q1–2015Q3; 16 euro countries; EM. Pearson correlations are used.

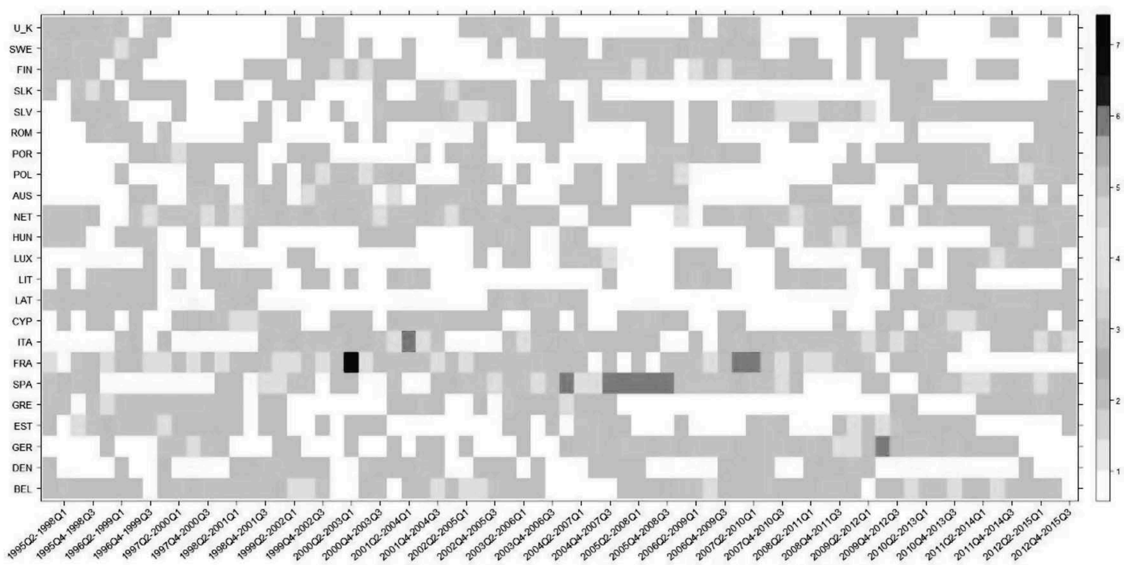

Figure 7. Number of connections for each country in the MST. MST is built over 3-year overlapping windows. Pearson correlations are used.

financial crisis, however, Germany increases its connectivity.

Figure 8 also addresses the issue of lead/lag relations between *GDPc* time series by plotting the delays at which correlation attains maximum values in the [−2,2] interval in the selected temporal windows, designating lags (leads) between country pairs by blue (red) squares. In most windows, the maximum correlation values occur more or less randomly in the whole range of values belonging to this interval. However, windows in the middle of the figure, which correspond to the period of global financial crisis, reach maximum correlation values in the zero-lag case. In fact, the panel corresponding to the 2007Q3–2010Q2 period displays almost perfect phase synchronization between *GDPc* co-movements in clear

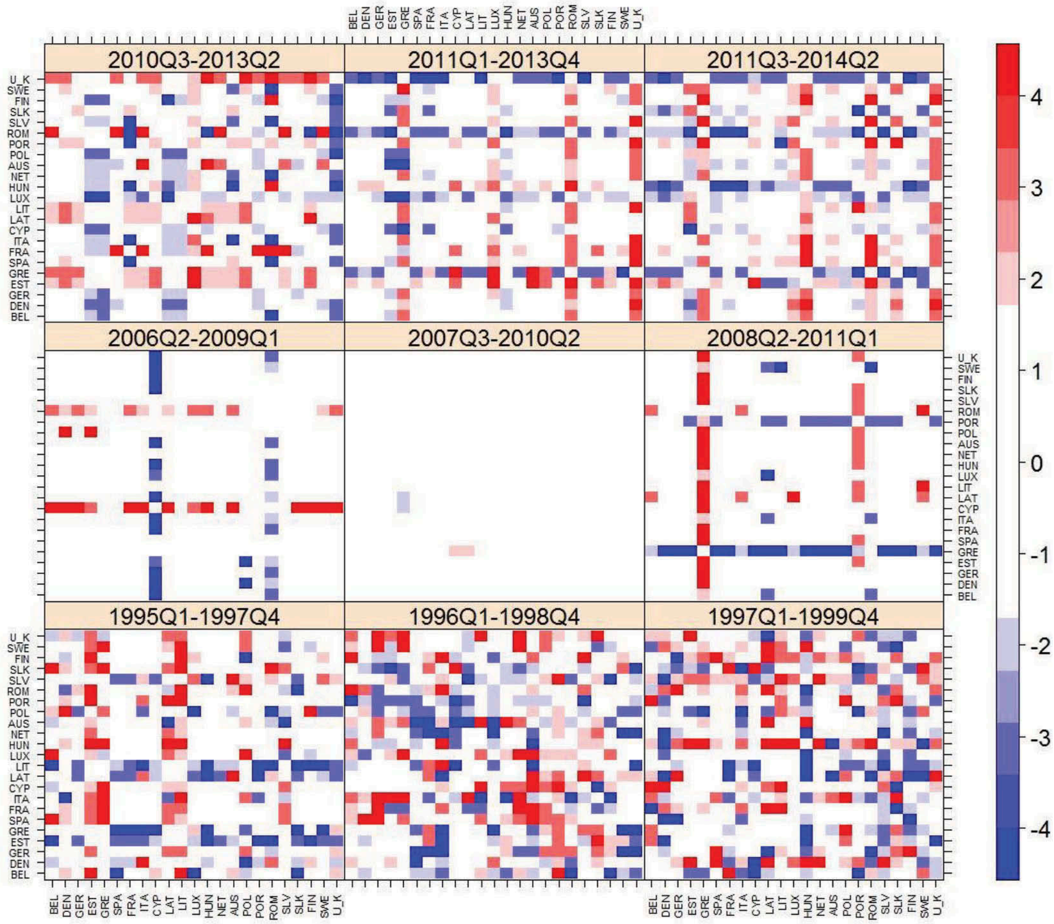

Figure 8. Pearson-based lead/lags maximum correlation, 3-year selected windows.

concordance with the cost minima shown in Figure 3, indicating that during this time of global shock, previous lag/leads disappear.

To complete the picture, we next examine whether the lead/lag relations between different national *GDPcs* (see Figure 8) imply a causal direction from one country to another. We make this determination by performing a Granger causality test (Equation 5) between every pair of countries in each temporal window and graphing the *F*-statistics that reach 5% significance in Figure 9. Because the temporal windows are short (12 values only), only two past values are inserted in Equation 2 (i.e. $L = 2$), meaning that the results reported here should be interpreted with extreme caution. Despite this caveat, however, these findings offer several valuable insights. First, in terms of Granger causality, not a single country seems to permanently affect the others. In fact, the large time variations observed suggest that direct causal interactions between country pairs are highly variable along the time sample. Nevertheless, in the middle windows that correspond to the global financial crisis, causality interactions clearly increase relative to other windows. Moreover, as lead/lag relations between countries vanish, co-movements become more phase synchronous and causality linkages increase. In this situation, macroeconomic spillover effects also increase (Antonakakis, Chatziantoniou, and Filis 2015), which raises the interdependence of the economic performance in different countries. Our use of rolling windows and network analysis enables us to describe this heterogeneous behaviour more accurately.

IV. Concluding remarks

By using co-movements in business cycles to illustrate network topology and its evolution, this

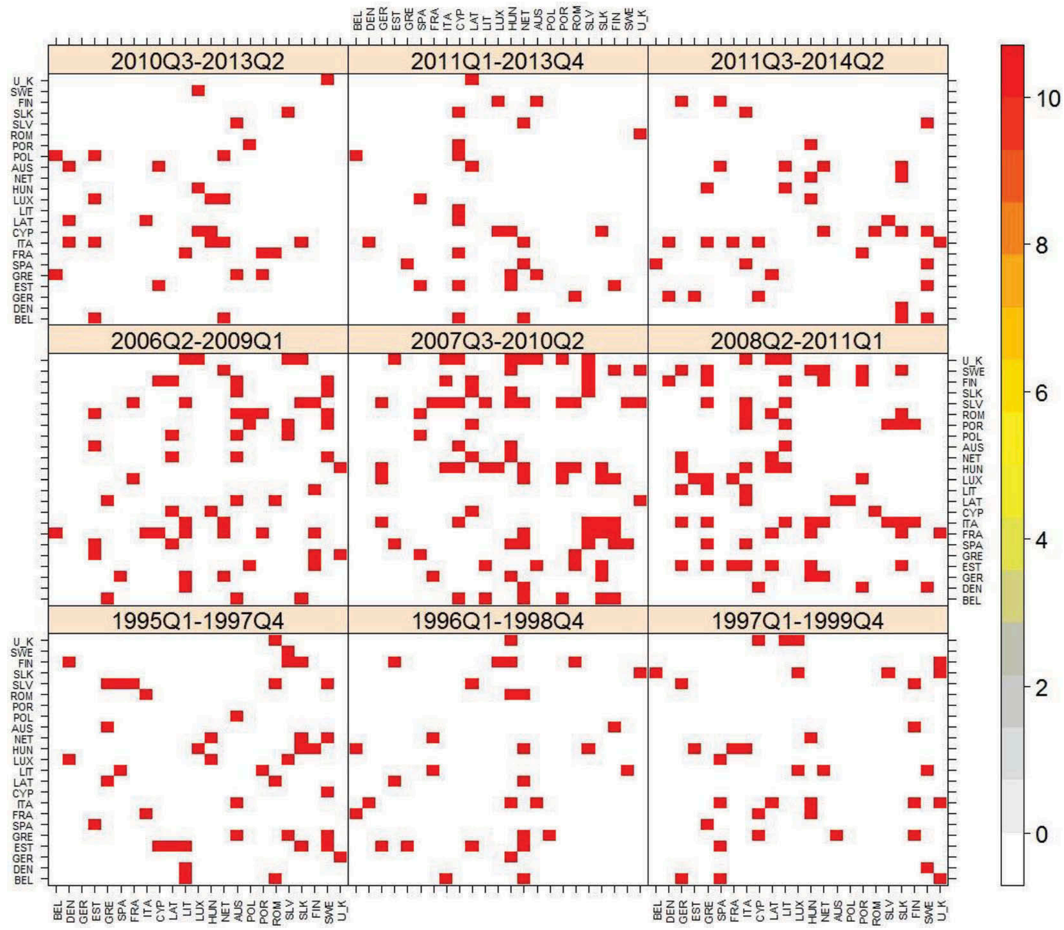

Figure 9. Granger causality, 3-year selected windows.

analysis identifies the connectivity diversification and synchronization that arises from economic interdependence between European countries. Our methodological approach, based on correlation matrix and network analysis (Mantegna 1999; Ortega and Matesanz 2006; Miśkiewicz and Ausloos 2010), is not only useful for analysing global co-movements, it offers a promising framework for summarizing synchronization in groups of countries. In particular, it enables us to provide highly accurate descriptions of interactions and connective heterogeneity across a system. This methodology could thus prove relevant for analysing the spillover effects of asymmetric shocks, and could provide useful information on monetary policy effects related to the connections and resilience of all elements in an economic system. For example, by using cluster analysis (Figure 2), we endogenously find evidence of at least two different European business cycle synchronization groups, as also reported by Camacho, Perez-Quiros, and Saiz (2008) and Aguiar-Conraria and Soares (2009). We further observe, however, that not only does a significant number of countries, including Greece, Portugal, Luxembourg and Poland, follow more independent output paths but that the long-term profile changes dramatically over the time sample.

It is particularly worth noting that the business cycle synchronization groups endogenously identified by our cluster analysis refute the exogenously derived division proposed elsewhere (e.g. Lehwald 2013) between core EMU countries like Germany, Austria, Netherlands and France and peripheral members like Portugal, Ireland, Italy, Greece and Spain. Rather, we find that for the whole period under study, both Italy and Spain are part of the core European output co-movements, which directly contradicts the findings of both Aguiar-Conraria and Soares (2009) and Darvas and Szapáry (2008), who respectively position Italy in the periphery with

Spain in the core and vice versa. In fact, our rolling windows analysis clearly places both countries (together with France) among the most connected nations, while other supposedly core countries like Germany and the UK appear to be following more independent business cycle paths.

When we trace the evolution of European business cycle synchronization by applying overlapping windows analysis to single countries and different country groups, we also observe patterns that are contrary to earlier findings. Within EM countries, for instance, synchronization has remained stable since 1999, indicating that, contrary to the claim by Papadimitriou, Gogas, and Sarantitis (2015), no output convergence has been induced by the euro. Not only does the global financial crisis lead to a sharp increase in co-movements as all the European countries slip simultaneously into recession (Matesanz, Ortega, and Torgler 2013), but the move towards more synchronism actually begins at the end of 2007 in anticipation of the economic slump. After 2009/10, however, a pronounced desynchronization process occurs because the subsequent recovery begins at different times (Gächter, Riedl, and Ritzberger-Grünwald 2012). It is also interesting that these processes of increased and decreased co-movement are strongly linked to an in-phase synchronization period seemingly characterized by more spillover effects from one country to another (in terms of economic performance). During the crisis period itself, Greece, Luxemburg and Portugal have a markedly negative effect on the cohesion of co-movements inside the euro zone.

Overall, our results confirm the existence of different synchronization dynamics in the output growth of both single nations and groups of countries, thereby echoing the notion of converging economic clubs in Europe (e.g. Baumol 1986; Quah 1997; Brida et al. 2011). At the same time, however, they highlight the difficulty of choosing an appropriate common monetary policy for current and future member countries. Our connectivity mapping, especially, suggests a need to deepen other structural characteristics of individual countries to reinforce the stability of the common currency area, an idea supported by the contagion of the Greek debt crisis to Southern European countries like Portugal, Italy, Spain and even France. It is also finally worth noting that it is our use of rolling windows and network analysis that permits us to document this inter-country heterogeneity with an accuracy not evident in prior research.

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Disclosure statement

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Appendix

List of countries.

European Monetary Union Members, EM (16 countries)

Austria, Belgium, Cyprus, Estonia, Finland, France, Germany, Greece, Italy, Lithuania, Luxembourg, Netherlands, Portugal, Slovakia, Slovenia, Spain.

Eastern European Non-EMU Members, EEN (4 countries)

Hungary, Latvia, Poland, Romania

Old European Non-EMU Members, OEN (3 countries)

Denmark, Sweden, United Kingdom