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On business cycles synchronization in Europe: A note on network analysis

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HIGHLIGHTS

- Dynamical networks of real GDP, European countries, annual 1950–2013.
- Correlation, connectivity, causality, leads/lags in dynamical windows over time.
- Increased synchronicity during the Euro period has not occurred but global financial crisis has peaked synchronicity.
- Lead/lag existence disappeared at the time of the financial crisis.
- Causality seems to spread from weak economic countries, such as Greece, to others during the Euro crisis.

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ABSTRACT

In this paper we examine synchronization in European business cycles from 1950 to 2013. Herein we further investigate previous and controversial results that arise from complex network analysis of this topic. By focusing on the importance of different configurations in the commonly used rolling windows and threshold significance levels, we find that selections are critical to obtaining accurate networks. Output co-movement and connectivity show no appreciable changes during the beginning of the Euro period, but rather dramatic jumps are observed since the outbreak of the global financial crisis. At this time, previous lead/lag effects disappeared and in-phase synchronization across Europe was observed.

1. Introduction

The debate about the costs and benefits of maintaining the euro area have moved to the forefront of academic and policy debate since the outbreak of the global financial crisis. The effectiveness of monetary policy and the benefits of the currency union depends on the extent to which member countries share some common economic characteristics related to the theory of optimum currency areas (OCA) pioneered by Mundell [1], McKinnon [2] and Kenen [3]. Among these properties, the similarity of the economic business cycle plays a central role for a common monetary policy to be optimal for all members, as the more synchronized are the members' business cycles, less costly should be giving up their independent monetary policy. It has been argued that participating in a currency union may itself lead to a higher level of synchronization by increasing economic liaisons, especially trade [4,5]. However, other arguments such as the advance of growing imbalances inside the currency union, different fiscal policies or different institutional settings of market regulations may negatively affect the evolution of synchronization among currency union members [6,7].

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Regarding this topic, a vast empirical literature has analyzed whether the European business cycles have become more synchronized since the euro was launched in 1999, whether there even existed a truly European business cycle, or which countries have achieved over time, or not, a higher level of synchronization [8–20, among many others]. Empirical results are not only inconclusive, but also controversial. For instance, Darvas and Szapáry [12] and Michaelides et al. [21], among others, have found some evidence that synchronization among euro countries has increased after the establishment of the euro area. On the other hand, inter alia, Weyerstrass et al. [13], Lehwald [16] and Crespo-Cuaresma and Fernández-Amador [6] show no increased synchronicity among all European countries after the euro, but increased interdependence is observed only for a group of them. Although the aim of the present paper is related to the use of network analysis, Gächter et al. [14], de Haan and Inklaar [22], BEPA [23] and Fidrmuc and Korhonen [24] offer good surveys of econometric business cycles synchronization in Europe.

Recently, a few papers have analyzed output co-movements by using network analysis [15,25,17,18,20]. Caraiani [25] analyzes business cycles synchronicity and causality in two different country samples, G7 and OECD, from 1970 to 2009. Xi et al. [17] use a pairwise entropy model to analyze synchronicity of the G7 group from 1960 to 2009 (quarterly data). However, these two studies apply complex networks analysis only for the whole period and, consequently, the dynamical evolution of co-movements is hidden. On the contrary, by using rolling windows, Gómez et al. [15], Antonakakis et al. [20] and Papadimitriou et al. [18] directly look into the dynamics of European business cycles co-movements over time.

In an intriguing paper, Antonakakis et al. [20] analyze synchronization over the long run, from 1870 to 2013, by using the novel Threshold-Minimum Dominating Set approach. They include 27 developed and developing countries. The highest synchronization is reached during the last period, which includes both the recent years of floating exchange rates regime and the global financial crisis after 2008 (1973–2013). A country-specific analysis is additionally carried out which reveals, for instance, that France, Belgium and Netherlands have been the most connected countries during the whole period. However, their study does not delve into these four periods (1875–1912; 1913–1944; 1945–1972 and 1973–2013) and therefore they are not able to separately identify the effects on output synchronicity of the recent financial crisis.

Gómez et al. [15] apply the Minimum Spanning Tree (MST) concept to quarterly GDP data for the 2000 to 2010 period. As is known, this methodology selects only the first, and more intense, link for every node in such a way that all of them are connected to the tree. The results show that the output synchronization of the euro area, as a whole, has remained stable over the last 10 years and has sharply increased after the outburst of the global financial crisis in 2008. Additionally, increasing heterogeneity in countries' co-movement degrees is observed, where some countries achieved high synchronization levels (Baltic Republics, Hungary, Slovenia and Iceland), while others behaved in a desynchronized fashion (Romania, Bulgaria and Greece).

The contribution from Papadimitriou et al. [18] focuses on this very same topic. They empirically study the evolution of business cycles co-movements of 22 European countries from 1986 to 2011 by analyzing annual GDP data. They build networks upon the minimum dominating set, which, in turn, is specified by a determined threshold (T-MDS). Additionally, standard network metrics applied to the T-MDS such as the total number of edges, the nodes' degrees, the network density or the numbers of dominant and isolated edges were calculated. This study introduces an interesting methodological discussion about both the importance of the size of the rolling window to be employed and the imposed threshold that obviously determines which will be the dominant and isolated edges. They adopt a 13-year window in order to split the entire time sample in two equal 13-year periods before and after the introduction of the euro in 1999. Regarding the employed threshold, the authors aim for a correlation level of 0.75. In their results, the authors found evidence in support of increased output synchronization in the post-euro era between all countries and especially between those of them that share the euro.

As observed, findings from network approaches provided by Gómez et al. [15] and Papadimitriou et al. [18] are to some extent conflicting. While Papadimitriou et al. [18] find increased co-movement during the euro stage in Europe starting in 1999, Gómez et al. [15] find a relatively stable synchronicity pattern up to the outbreak of the financial crisis at the end of 2008 and, then, a sharp jump in connectivity and correlation levels between most European countries. Nevertheless, two different network approaches were employed in these studies and they are not methodologically comparable.

In this work we take a step forward in the analysis of the European economic cycles' synchronization from a network perspective. Specifically, three different issues are addressed. Firstly, we want to differentiate the effects of the launching of the euro in 1999 from the effects associated with the financial crisis originating in 2008. The choice of window size lengths is critical to this issue. Secondly, we are interested in the effects of the exogenously imposed correlation thresholds levels over the network topology. Thirdly, true underlying causality between GDP co-movements was assessed by using cross-correlation and Granger methodologies. To approach these issues, we zoom in on the data by computing network properties for different threshold significance levels and window sizes. Additionally, the effects of thresholds have been studied in both the minimum spanning tree and the minimum spanning forest (both concepts are explained in the methodology section).

Two main results arise from our analysis. Firstly – and somehow independent of the window size, the filtering method and the similarity measure employed – there exists an apparent intensification in correlations and connectivity when 2009 is included in the time window. On the contrary, at the time of the launching of the euro in 1999, no significant change is observed. In this fashion, the sharp change observed in correlation and connectivity seems to be more related to the outbreak of the global financial crisis at the end of 2008 rather than linked to the euro appearance, in line with other contributions [26–28,13]. Additionally and closely related to this issue, we find almost perfect in-phase synchronization at the time of the financial crisis destroying previous and random out of phase correlations. The use of the Granger causality allows to not only discard most of the spurious direct GDP relationships, but also to uncover the importance of particular

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Table 1
21 selected countries and acronyms.

Eurozone countries		Non-Eurozone countries
Austria (AUS)	Italy (ITA)	Denmark (DEN)
Belgium (BEL)	Luxemburg (LUX)	Iceland (ICE)
Cyprus (CYP)	Malta (MAL)	Norway (NOR)
Finland (FIN)	The Netherlands (NET)	Sweden (SWE)
France (FRA)	Portugal (POR)	Switzerland (SWI)
Germany (GER)	Spain (SPA)	Turkey (TUR)
Greece (GRE)		UK (U_K)
Ireland (IRE)		

countries' GDP movements, as for instance in the case of Greece, which seems to spread its dynamics over other countries. An additional finding that arises from this paper is that dynamical network analysis illustrates the complexity and heterogeneity of connections over time in more detail.

The rest of the paper is organized as follows. Section 2 describes the database, methodology and numerical methods. Section 3 reports our main results. Finally, Section 4 interprets our findings and discusses their statistical and economic implications.

2. The dataset

The dataset consists of yearly real gross domestic product (GDP) as reported by the Groningen Growth and Development Centre at the University of Groningen (data are available online in the institution's Total Economy Database: http://www.ggdc.net/databases/ted.htm). GDP is presented in 1990 U.S. dollars converted into Geary Khamis PPPs to allow international and time comparisons across the entire database. The chosen time interval, from 1950 to 2013, covers the entire life period of the European Union integration process up until the global financial crisis started in 2008. We have included 21 countries (see Table 1): 14 current eurozone countries and 7 European countries not belonging to the euro area, Q3 in line with the work of Papadimitriou et al. [18].[1] Rates of growth, *rGDP*, have been calculated in the usual way, as follows: Q4

$$rGDP_i(k) = \frac{GDP_i(k+1) - GDP_i(k)}{GDP_i(k)} \quad (1)$$

where i runs from 1 to 21 and k runs from 1 to 63 (64 years without the year 1950, which is not actually used in the derivative of Eq. (1)). Therefore, our complete dataset is a matrix of 63 rows (yearly rates of growth) and 21 columns (countries).

3. Methodology

3.1. Network, minimum spanning tree and minimum spanning forest

The basic building blocks in any complex network are the nodes and the links that connect them. As is most common, the Pearson correlation coefficient between two *rGDP* time series was calculated as an estimation of the link strength between them. Once a correlation matrix was obtained, the absolute value of those statistically significant correlation estimates, at a particular level (see below), was exclusively used as the links' strength between the countries GDPs time series. Finally, the density of links (DoL), i.e., the ratio of the actual number of links in the network to the number of all possible links, was calculated in the so constructed network.

In order to simplify the usually complicated fully connected network, the minimum spanning tree/forest method, a cluster analysis technique, was employed. The minimum spanning tree (MST) has no loops in its links along the nodes and, moreover, is the tree with minimum total length, thereby displaying the most "important" connections of the underlying network. To construct the MST, a measure of dissimilarity, as opposed to a measure of similarity like the correlation, is needed between the network nodes. This is commonly achieved by defining the "distance" between two time series $\mathbf{x} = x_k, k = 1, N_{dat}$ and $\mathbf{y} = y_k, k = 1, N_{dat}$, corresponding to two different $rGDP_i(k)$ as follows

$$\mathrm{d}(x, y) = \sqrt{2(1 - \tau_{x,y})} \quad (2)$$

where $\tau_{i,j}$ is the absolute value of the Pearson correlation coefficient. Using the nodes (countries) and the corresponding distances between them, the Kruskal algorithm is employed to build the tree (for a more detailed explanation about the construction of the MST see, for instance, Mantegna [29] and Ortega and Matesanz [30]). When the original network is connected, i.e. a path exists between every two different nodes, a connected tree with no loops and minimum length, called an MST, is obtained. On the other hand, if the original network is not connected, that is, has isolated nodes, it is called minimum spanning forest (MSF). Therefore, three kinds of networks are employed: threshold networks, MST and MSF. In this way, the traditional shortcoming of the no-loop restriction in the MST approach is overcome.

[1] Our study has sixteen countries in common with Papadimitriou et al. [18], while five of them are different.

3.2. Lead–lag relationships between rGDP time series

Does a low value of the Pearson correlation always imply uncoupled behavior between two different *rGDP* time series? Certainly not, because if two time series were highly correlated but shifted in time with respect to one another, they would have a low zero-lag correlation but a high time shifted correlation. This fact would imply that one is leading/lagging the other. In order to deal with this situation, two different calculations were implemented.

On the one hand, correlation values were evaluated also for the case of temporal shifted time series up to two temporal windows (two years). We then selected the maximum value of the correlation (the absolute value) in that window. Note that this procedure provides five correlation values at $\Delta t = -2, -1, 0, 1, 2$, with $\Delta t = 0$ being the usually employed. Both correlations, $\Delta t = 0$ and the maximum of correlation in the $[-2, 2]$ interval will be employed (see below).

Granger causality was calculated in the search for potential causality mechanisms. Based on Wieners' ideas [31], Granger Q5 implemented (Granger, 1969) a procedure to test whether a causal relationship between two time series exists or not, formulated under the formalism of linear auto-regressive models. Given two time series $\mathbf{x} = x_k, k = 1, N_{dat}$ and $\mathbf{y} = y_k, k = 1, N_{dat}$, the Granger Causality (GC) examines whether future values of $\mathbf{x}$ are better predicted by using past values of both $\mathbf{x}$ and $\mathbf{y}$, instead of using exclusively past values of $\mathbf{x}$. If this is true, we may say that $\mathbf{y}$ *Granger cause* $\mathbf{x}$. To numerically implement these ideas a linear auto-regressive model of order L is fitted 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 standard errors ε_x and ε_y such that

$$\begin{aligned} x_k &= \sum_{i=1}^{L} a_i x_{k-i} + \varepsilon_x \\ x_k &= \sum_{i=1}^{L} a_i x_{k-i} + \varepsilon_x + \sum_{i=1}^{L} b_i y_{k-i} + \varepsilon_y. \end{aligned} \tag{3}$$

If the second prediction *is better* than the first one, we may say that past values of $\mathbf{y}$ influence present values of $\mathbf{x}$. To quantify "better" in a statistical sense, a comparison between ε_x and ε_y is performed, for instance by using,

$$GC_{y\to x} = \ln \frac{\operatorname{var}(\varepsilon_x)}{\operatorname{var}(\varepsilon_y)} \tag{4}$$

such that $GC_{y\to x}$ is non-negative and the greater the $GC_{y\to x}$ is, better is the fit of the combined model, thus implying a causality from $\mathbf{y}$ to $\mathbf{x}$. Statistical significance of this equation can be assessed using the Fisher test

$$F = \frac{\frac{RSS_x - RSS_y}{L}}{\frac{RSS_y}{N_{dat} - 2L - 1}} \tag{5}$$

where RSS_x and RSS_y are residual sums of squares of models $\mathbf{x}$ and $\mathbf{y}$, respectively.

In our particular case, both time series $\mathbf{x}$ and $\mathbf{y}$ will be replaced by *rGDP* (Eq. (1)) belonging to two different countries i and j. A statistical significance level of 5% in evaluating the F-statistic of Eq. (5) has been used.

3.3. Time windows analysis

This is an important point in the present work. There exists a tradeoff between the window length and the statistical robustness of the calculation performed on it. For instance, in using the Pearson correlation, the statistical significance of the calculated estimate is given by the Fisher's r-to-Z transformation [32]. This means that for a small number of data points – years in our particular case – ($N < 10$) the correlation estimates must be greater than 0.6 in order to be statistically significant at a 5% level. Selecting long temporal windows leads to more robust calculations, but overlooks finer details. The use of short temporal windows, on the other hand, may uncover more details but without the required statistical significance. To examine the effects of short temporal windows on network measures, we fixed the temporal window length at nine years. The motivation behind this particular choice is the use of a temporal window length that includes the euro launch but simultaneously excludes from the analysis the global financial crises effects, such as the 1999–2007 period. The aim, therefore, is to discriminate the euro launch from the financial crisis effects. In this sense, the choice of a 9-year window is a pragmatic decision not directly related to the traditional study of theory and econometrics of business cycle research [33–35].[2] Additionally, we focus on output rather than other important variables typically employed in business cycle research (such as, for instance, consumption or industrial production) because we are fundamentally interested in co-movements for the whole European economic system, which are more linked than other variables to the global economic effects of the common monetary policy in the eurozone.

[2] We have repeated calculations for 13 and 15-year windows. For the purpose of this paper, results remain identical. Figures corresponding to these calculations can be directly obtained from the authors.

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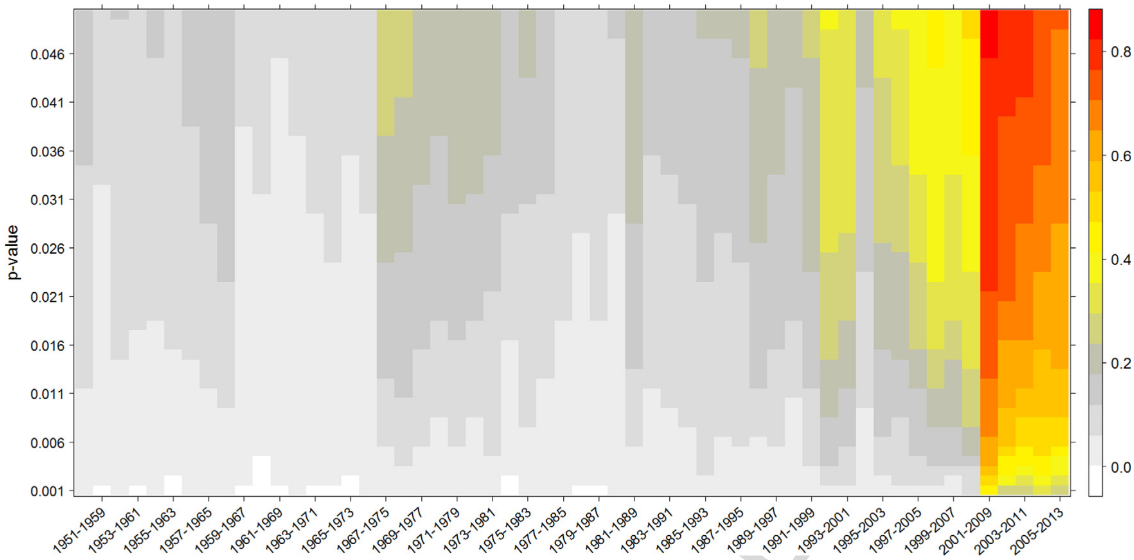

Fig. 1. Density of nodes. 9 year window. 1950–2013. Similarity measure; Pearson correlation coefficient. Threshold significance level from 0.001 up to 0.05.

The network temporal behavior of GDP co-movement was then studied throughout the entire 1950–2013 period, in overlapping windows of nine years, with one-year increments forward in time. The correlation matrix was calculated in each temporal window and, using this information, two different types of networks were constructed. First, by using the entire correlation matrix, the distance matrix (Eq. (2)) was calculated and the MST was obtained. The sum of the distances of all the links in this tree was then calculated.[3] We have labeled this sum *MST cost*. Second, by selecting from the correlation matrix exclusively those correlations with p-values lower than a particular threshold, a network was constructed using the absolute value of those selected correlations as the links strength. Finally, the DoL of the constructed network was calculated. This procedure was repeated by varying the p-values threshold in the range of 0.001–0.05, in steps of 0.005, that is; 0.001, 0.006, 0.011, etc. Note that this procedure will certainly create isolated nodes, giving rise to disconnected networks as lower p-values thresholds are imposed.

4. Empirical results

A level plot of the DoL is displayed in Fig. 1. For each nine-year temporal window (period in the x-axis) and a particular threshold in the p-value (y-axis), the value of the DoL corresponding to the constructed network under that condition is colored. Redder (paler) colors imply higher (lower) DoL. Moving upwards, the threshold significance level increases from 0.001 to 0.05.

As is readily apparent, the DoL increases as we move upwards, allowing more available links for network construction, but at the cost of a lower statistical significance. This fact is indeed a general rule in constructing networks from empirical data. On the other hand, the DoL also increases as we move from left to right, that is, from 1951 to 2013, at almost any significance level. Remarkably, the increase in the DoL is accelerated at the beginning of the nineties, particularly evident at higher p-values. Two different regimes seem to drive synchronization in the network. The first one begins approximately in 1990, lasting until the year 2001, and the second one starts at that same year up until 2013. The period encompassing the years 2001–2013 shows an abrupt jump in connectivity, most probably caused by the onset of the financial crisis at the end of 2008. This is apparent in the sudden transition, at p-values greater than 0.02 for instance, in the DoL from a value of 0.4 in the 2000–2008 period, to a value close to 0.8 in the next period, 2001–2009, which encompasses the onset of the financial crisis. This value in the DoL is nearly sustained in the remaining periods.

Fig. 2 plots both the cost of the MST, calculated by using the zero lags correlation fully connected network without imposing p-values thresholds (continuous line), and the MST cost built in the same way but taking into account the maximum of correlation in the $[-2, 2]$ interval (dashed line), as explained in the methodology section. In this figure, a sharp increase in cross correlations is clearly observed, i.e. decreasing MST cost at the time of the oil crisis around the mid-seventies (1968–1976) and at the current financial crisis from 2009 onwards. In fact, the highest level of cross correlations appears at the outbreak of the financial crisis, when 2009 is included in the time window. Note that in this case, similar results

[3] By using this approach, a fully connected network is obtained and if all of the distances are different – an almost certain fact in this kind of data – the tree constructed in this way most likely is an MST.

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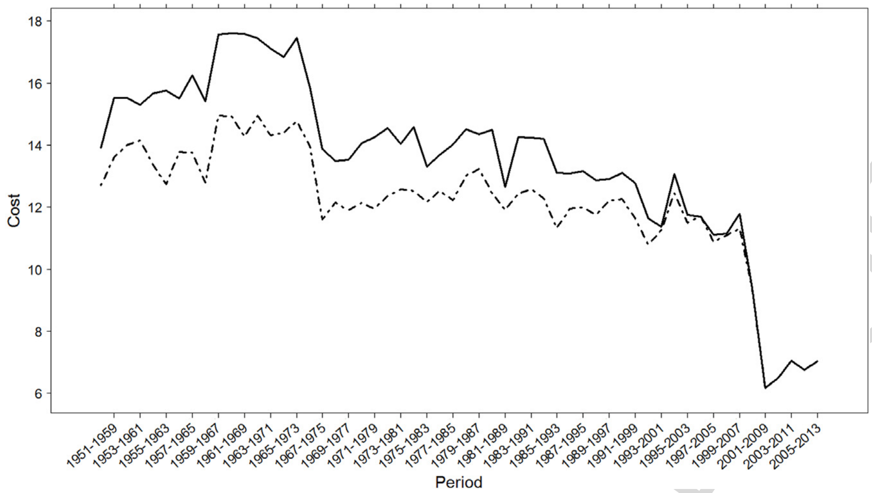

Fig. 2. MST Cost. 9 year window. 1950–2013. Similarity measure; Pearson correlation coefficient. No thresholds involved. Dashed line takes into account maximum correlation including [−2, 2] lags. Continuous line includes no lags.

to those appearing in Fig. 1 are also observed: two regimes drive synchronization in the network. A first regime seems to slowly increase synchronization from the 1985–1993 period until the 2000–2008 period. At this moment synchronization dramatically increases in the network, sharply lowering the MST cost in both cases of zero and maximum lags. Additionally, we can observe that the shape of the evolution of the MST cost is almost identical for both the zero lag and the lag of maximal correlation. Both lines follow similar patterns, with the line corresponding to the case of lags of maximal correlation being lower than that corresponding to the zero lag correlation. This is readily understood since correlations corresponding to lags of maximal correlation are always greater than or equal to correlations in the zero lag option. However, both lines approach one another during their evolution until approximately the 1999–2007 period, where both of them follow the very same path. Whatever kind of leads/lags may have existed between countries' GDP growth before the 1993–2001 period, it nonetheless has disappeared since then. In this sense, since the launching of the euro, and especially when taking into account the global financial crisis, zero lag dephasing between GDP co-movements is readily apparent.

A level plot of the costs of both the MST and MSF is displayed in Fig. 3. For each nine-year temporal window (period in the *x*-axis) and a particular threshold in the *p*-value used to construct the network (*y*-axis), the cost of the MST or MSF derived from it is colored. Dashed lines encompass the area where the derived trees from the original networks are MST, that is, where the network has no isolated nodes. The remaining area corresponds to MSF, that is, trees with isolated nodes. Note that the color scale in this figure, based on distances, is somehow the inverse of the one used in Fig. 1, which is based on correlations. Almost regardless of the *p*-value threshold, this result supports the ideas formerly expressed in Figs. 1 and 2; the onset of the global financial crisis in 2009 produces the greatest connectivity and synchronicity in the European output network. However, taking into account extremely exigent *p*-values thresholds (such as those from 0.001 to approximately 0.011) yields non-fully connected trees as shown in this figure.

In order to provide a clear vision of what we are actually doing, two particular examples are depicted in Fig. 4. The first case, the upper-left panel, corresponds to the 1979–1987 period. The network has been constructed by imposing a correlation significance of 0.026. As observed, it leaves several countries, such as, France, Spain, Iceland, Denmark and Ireland, outside the main network. The use of the Kruskal algorithm produces an MSF, the upper-right panel, with the same countries not connected to the main tree. The other particular case, corresponding to the 2001–2009 period, shows a densely connected network with no isolated countries. From an economic point of view, the first selected period, 1979–1987, might be considered a tranquil time in terms of global economic shocks,[4] while the next one, 2001–2009, includes the outbreak of the global financial crisis. Comparing both networks we observe much greater synchronization and no isolated nodes during the last period, while the 1979–1987 period reveals less co-movement and countries with more isolated output dynamics, in line with previous results.

The issue of lead/lag relationships between *rGDP* time series was addressed in the following way. Fig. 5 plots those delays at which correlation attains maximum values in the interval [−2, 2], during selected temporal windows. Blue (red) squares mean lags (leads) between the involved pair of countries. In most of the windows, maximum values of correlations are attained more or less randomly in the whole range of values belonging to this interval. This fact explains why in Fig. 2 the cost of the MST constructed using these values is lower than the one corresponding to the case of zero lag.

[4] Although 1987 is very well known because of the black Monday stock market crash (19th of October), which is the largest drop during a market day ever, the economies did not experience significant GDP contractions. For instance, the US increased its GDP by 3.5% in 1987 and more than 4% the next year.

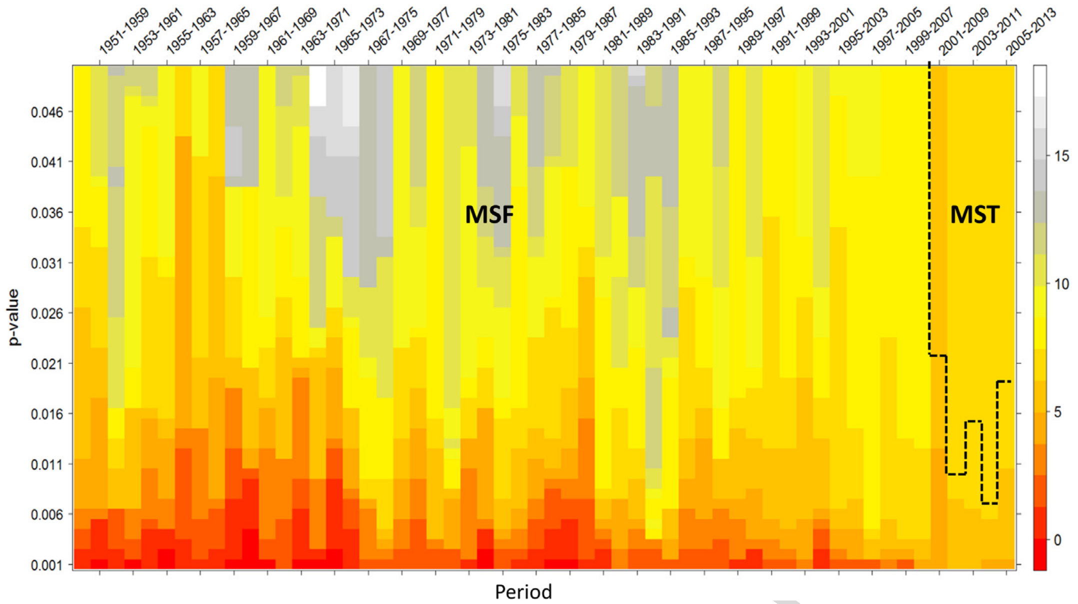

Fig. 3. Costs of the Minimum Spanning Tree (MST) and Forest (MSF): Under the MSF region, the trees are composed of isolated nodes. Under the MST region, the trees are connected. X-axis corresponds to the 9 year windows, ranging from 1950 to 2013. A Pearson correlation coefficient is used. Threshold significance level (y-axis) ranges from 0.001 up to 0.05.

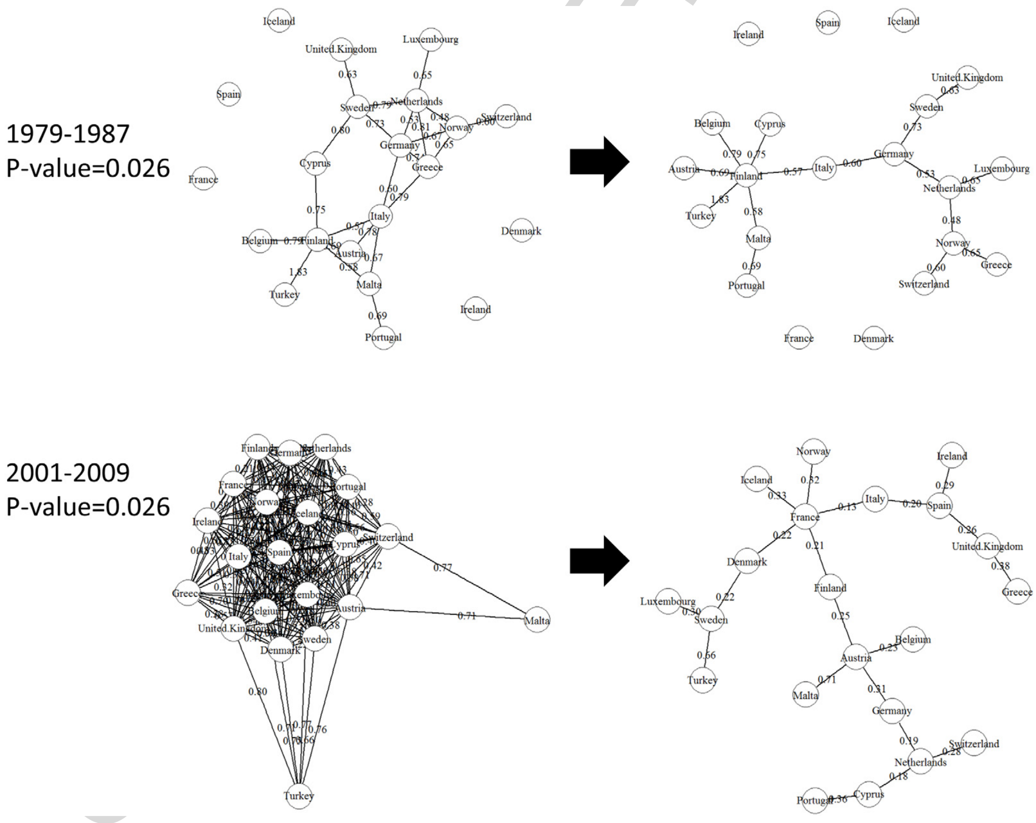

Fig. 4. Networks, minimum spanning tree and minimum spanning forest. Pearson correlation coefficient, Significance threshold 0.026. (a) 1979–1987, (b) 2001–2009.

Also, as formerly demonstrated, during the last periods, in particular those plotted in the bottom right portion of Fig. 5, 2001–2009 and 2005–2013, maximum correlation values are reached for the zero-lag case. This implies that during the

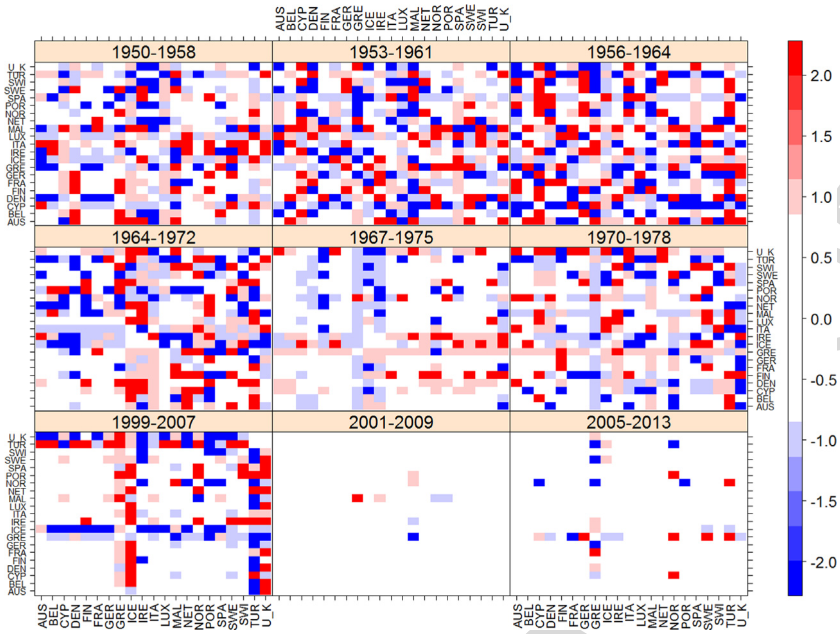

Fig. 5. Leads/lags maximum correlation. 9 years selected windows. Similarity measure; Pearson correlation coefficient.

last periods, an overall synchronous behavior between GDP co-movements existed across country economies. In fact, the panel corresponding to the 2001–2009 period in Fig. 5 displays almost perfect phase synchronization between the GDP co-movements, in clear concordance with the cost minima in Fig. 2.

We next address the question of whether the lead/lag relationships between countries' GDP displayed in Fig. 5 are effectively produced by stable and permanent underlying driving interactions or, on the other hand, if they are purely spurious. In order to delve deeper into this question, the Granger Causality (Eq. (5)) test was performed between every pair of GDP time series in each temporal window. Only F-statistics with significance at a 5% level are displayed in Fig. 6. Because of the so-short temporal windows length – twelve values – used, only two past values were inserted into Eq. (2), that is $L = 2$. Thus, the results presented here should be taken with extreme caution. Nonetheless, some insights are worthy of mention. First of all, it seems that most of the lead/lag relationships appearing in Fig. 5 show large time variations and consequently causal direct interactions between pairs of countries are highly spurious along the time sample. This is most clear in the first seven temporal windows selected (from 1950–1958 to 1999–2007). Although many shifts – from the zero-lag – in the correlation maxima are apparent in Fig. 5, only a few causal relations are detected in Fig. 6. The last period (2005–2013) deserves a special mention, however. Only two countries appear out of phase from the rest, Greece and Norway (blue and red squares in the last panel of Fig. 5). Looking at the bottom-right corner of Fig. 6 (2005–2013) one can observe that Greece in fact seems to be the country that affects almost all of the other economies (vertical red line of squares). To show a clearer picture of the situation in that temporal window, Fig. 7 displays the actual causality relations, with Greece, at the center, leading the GDP movements.

This large lead/lag and causality dynamical variability and its response to important economic effects seem to be connected to the spillover effects among countries as suggested by Antonakakis et al. [19]. By employing rolling windows and networks, we are able to clearly observe this heterogeneous behavior more accurately.

5. Conclusions

In this work we revisited the evolution of European economic cycle synchronization by using a network approach, following previous studies on this topic (for instance, Artis and Zhang [8], Massman and Mitchell [10], Darvas and Szapary [12], Weyerstrass, et al. [13], Gómez et al. [15], Caraiani [25], Papadimitriou et al. [18], Antonakakis et al. [19], among many others). Our main aim being to discuss and interpret the obtained results when different filtering methods, window lengths and statistical significance were used on the same historical dataset. Two main results were found.

Firstly, a sharp increase in correlations and connectivity in the network is observed during the year 2009. Interestingly, this increase in the synchronization of *rGDP* co-movements appears somehow independently of the employed window size, filtering method and/or similarity measure. Not only an increase in the correlation of the *rGDP* co-movements exists, but also the disappearance of time shifts between the time series. On the contrary, at the time of the launching of the euro in 1999, no significant changes are observed. Moreover, the euro launching at the end of the nineties seems to be embedded in a previous and slow trend of increasing synchronization since the eighties, at least, as can be observed in Fig. 2. By the

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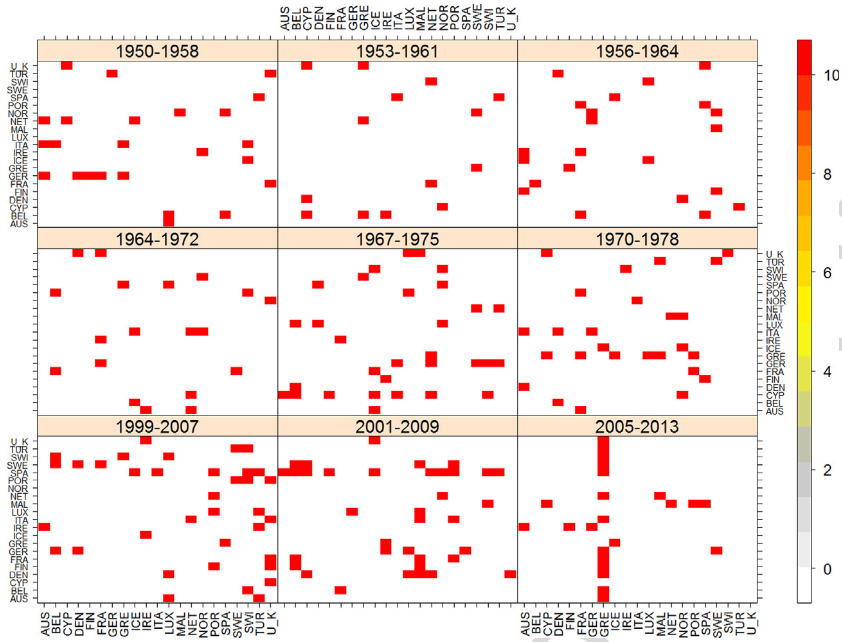

Fig. 6. Granger causality. 9 years selected windows.

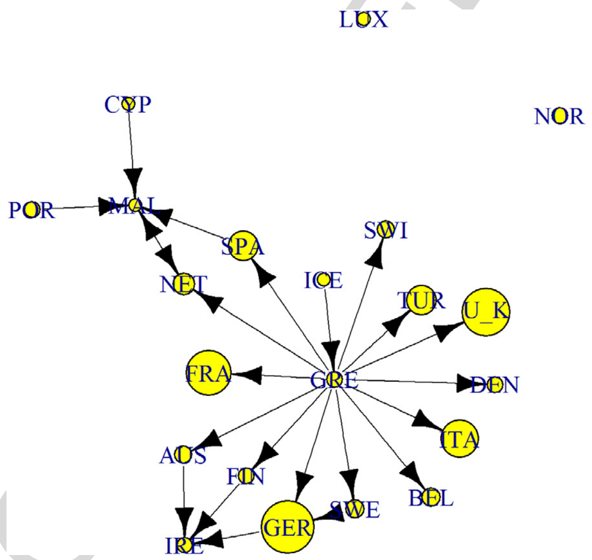

Fig. 7. Granger causality. View of the last window, 2005–2013.

last years of the past decade however, an abrupt change in the way countries synchronize appears, tightening GDP co-movements. This dramatic change observed in both the correlation and connectivity appears to be related to the outbreak of the global financial crisis rather than linked to the history of the euro, in line with other contributions [26–28,13].

Secondly, it is important to note that the use of rolling windows allows uncovering not only of the synchronization dynamics but also the temporal existence of leads/lags or in — phase co-movement stages. In this fashion, zero lag dephasing between GDP co-movements is readily apparent at the time of the outbreak of the financial crisis, which destroys previous leads/lags. Causality at this time shows Greece being the country to most affect the rest of the economies.

Dynamical network analysis illustrates in more detail the complexity of output co-movements in the euro area. It confirms, additionally, the heterogeneity of connections over time, especially when large economic shocks are involved. As long as connectivity, synchronicity, causality and in-phase correlations are observed at the time of economic shocks, macroprudential stabilization policies should be designed. Our causality analysis additionally shows that Greece, one of the smallest economies in Europe, affects economic performance across Europe.

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