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Sovereign public debt crisis in Europe. A network analysis

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HIGHLIGHTS

- Dynamical networks of government debt as a percentage of GDP; quarterly, 2000–2014.
- Cophenetic correlation to analyse persistency of hierarchical trees during the financial crisis.
- High synchronicity and connectivity and low number of communities at the time of the crisis.
- Less diversification and more centralized network arrangements.
- New network organization after the financial crisis arranged by public debt levels.

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ABSTRACT

In this paper we analyse the evolving network structure of the quarterly public debt-to-GDP ratio from 2000 to 2014. By applying tools and concepts coming from complex systems we study the effects of the global financial crisis over public debt network connections and communities. Two main results arise from this analysis: firstly, countries public debts tend to synchronize their evolution, increasing global connectivity in the network and dramatically decreasing the number of communities. Secondly, a disruption in previous structure is observed at the time of the shock, emerging a more centralized and less diversify network topological organization which might be more prone to suffer contagion effects. This last fact is evidenced by an increasing tendency in countries of similar level of public debt to be connected between them, which we have quantified by the network assortativity.

1. Introduction

The bursting of the US housing bubble triggered the bankruptcy, or the need to be rescued, of large and well reputed banks and insurance companies in many developed countries. Especially since the collapse and bankruptcy of Lehman Brothers on September 2008, credit flows dried up, lender confidence dropped with investors repatriating funds to domestic markets and world economies dipped into recession because of international and domestic aggregate demand plummeted [1,2], Regardless of policy action, especially in the US, had treated to contain the symptoms of the financial turmoil, the crisis spillovered from "Wall Street to Main Street" [3]. At the beginning of the financial crisis however the focus was on the actions of Central banks to address the financial shock and expansionary measures to reactivate the economies, while there was little concern about public debts. In late 2009, it was clear that the scale and length of the recession increased the perspectives of banking losses on bad loans and also had a negative impact on sovereign debts values [4]. Additionally, some countries

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reported larger-than-expected increases in fiscal deficits, Ireland and Spain for instance. After October 2009, the new Greek government recognized larger fiscal deficit for previous years than those previously announced and a new budget deficit forecast for 2009. This combination of facts definitely moved the focus of the crisis to European sovereign debts from 2010 onwards [5].[2]

Since the beginning of the financial crisis the euro area as a whole elevated its public debt ratio from 67.4% in the first quarter of 2008 to 93.9% of their Gross Domestic Product (GDP) in the first quarter of 2014. In the same period, Greece went from 107.9 to 174.1%. Most striking, Ireland increased this ratio from 27.5 to 123.7%[3] in this short period of time. Other countries such as Italy, Belgium, Spain or France have observed high and increasing levels of public debts-to-GDP ratios as the crisis was going on. On the other side, Finland, Germany or Austria experienced softer deterioration on their public debt positions while other European countries such as Norway experienced a reduction in its public debt from almost 43% during 2008 to 29% at the end of the period. However, from the beginning of 2000 till the end of 2007 debt-to-GDP ratios were more stable and slightly decreasing in most countries of Europe (see Fig. 1). As Lane [5] claims European countries have quite different debt histories.

Recently, a few papers have focused on the European debt crisis by analysing the dynamics of daily government bond yields (e.g., Refs. [17–19]) and the network topology of the public debt itself [20].

Dias [19,18] uses maximum spanning trees to analyse the topological properties of government bond rates' markets in different periods including the European debt crisis. In their paper, Kantar et al. [20] investigate hierarchical and topological structures by using the minimum spanning tree (MST) approach in public debt as a percentage of the gross domestic product from 2000 to 2011. These papers have shown that European countries have formed different clusters regarding the dynamics of their public debts during the global and financial current crisis. The most and the less affected countries form groups during the sovereign crisis but they do not do so before with respect to government bond yields [20,19,17]. Especially the group of the most affected countries (the so called PIGS—Portugal, Ireland, Greece and Spain) get closer in their government bond yields dynamics. Additionally, these groups have moved away from each other as the crisis moves on [18,19]. These results suggest different network dynamics related to government debt position as crises events affect the economies involved in the system. All of these works are in line with recent advances in the econophysics field in which tools and concepts from complex systems have been applied to different economic issues. For instance: finance ([21–24], among hundreds of studies), economic growth dynamics [25,26], commodity prices [27,28], interest rates (e.g., Refs. [19,18]), trade (e.g., Refs. [29,30]) and exchange rates (e.g., Refs. [31,32]).

Within the above framework we construct a network of public debt-to-GDP quarterly ratios from 2000 to 2014, belonging to 29 European countries. We study networks dynamics by means of sliding windows forward in time. We extend previous works on this issue (e.g., Refs. [20,19,17]) by analysing the temporal stability of the debt-to-GDP network.

As the financial and European debt crisis is included in our sample, this paper contributes to understand the dynamics of the public debt evolving network in times of crisis. Three conclusions arise from this analysis. Firstly, we observe during the crisis that countries' public debts tend to synchronize their changes, increasing global synchronization and hence dramatically decreasing the number of communities in the network. Secondly, as a result, a disruption in the previous structure is observed at the time of the financial crisis, giving rise to a homogenization in the member's co-movements, producing in this way a network topological organization highly susceptible to spread the effects of the crisis among the countries. Finally, at the onset of the financial crisis the new network arrangement that appears seems to be directly related to the debt-to-GDP level itself which clearly puts into difficulties for controlling the public debt dynamic.

Next section presents the dataset and numerical methods employed in the analysis. Section 3 presents the main results and, finally, Section 4 summarizes and discusses previous results. At the end of the paper, a supplementary section have been included providing methodological details, additional figures and a summary of findings (see Appendix A).

2. Methodology

2.1. Data

The dataset, borrowed from the Eurostat statistics database (http://ec.europa.eu/eurostat), consists of quarterly public debt as percentage of country GDP, encompassing the period 2000 (Q1) to 2014 (Q1). We have included 29 European countries; 28 members of the European Union at the beginning of 2014 and Norway. Croatia was the last country joining the European Union on the first of July 2013. However, at the beginning of entire period, Q1 of 2000, only fifteen were members of the European Union. Eighteen countries shared the Euro at the beginning of 2014, including Latvia which joined the first of January 2014 (Lithuania joined the Euro on January 2015). At the time of launching the Euro in 1999 just eleven countries

2 Economic literature on different topics of the financial crisis and debt crisis is vast. Among other topics we can find the accumulation of macroeconomic, fiscal and financial vulnerabilities prior to the financial crisis itself [6,7], aspects related to what happened in different asset markets ([3,8], among others), policy studies, transmission of shocks and asset pricing [9,10,2], the European debt crisis [5,4,11]. On the other side, econophysics literature has analysed different aspects such as: the structure and resilience of financial networks affected by extreme event [12–14], the network structure and systemic risks [15,16].

3 Data from last quarter 2013.

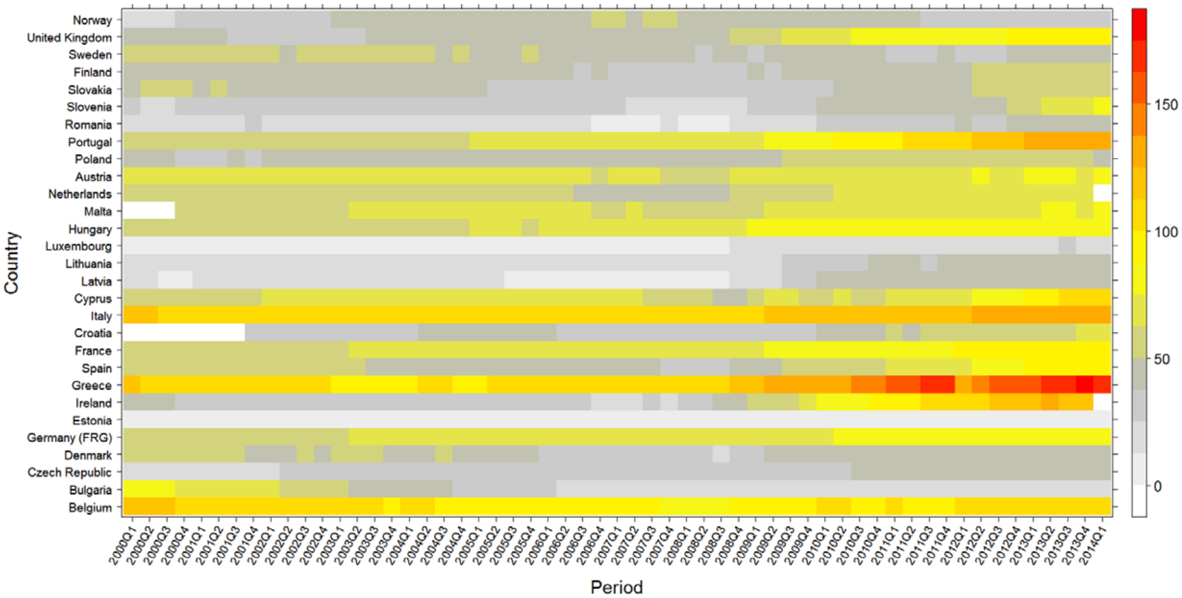

Fig. 1. Public debt-to-GDP ratio. European countries, quarterly. 2000Q1–2014Q1.

joined the common currency followed by Greece in January 2001. Independently of the time of inclusion to both the Euro area and the European Union we have included all countries. Fig. 1 shows a public debt-level plot for the entire period and countries. As observed, most of the countries have increased their levels of public debts in terms of the GDP from 2009. Greece, Ireland, Portugal, Italy and Belgium are the most indebted countries in Europe at the end of the period.

Differences of debts, dD, are calculated in the usual way, as follows:

$$dD_i(k) = D_i(k+1) - D_i(k) \tag{1}$$

where i runs from 1 to 29 (number of countries), and k runs from 1 to 56 (57 quarters minus 1).

2.2. Numerical methods

2.2.1. Cluster analysis: Hierarchical trees and cophenetic correlation

Following usual practice in econophysics [21,33,25] to quantify the interdependence degree of synchronization between two time series, the Pearson[4] cross-correlation coefficient, ρ was calculated between every pair of dDs.

Given two time series $\boldsymbol{x}_i = x_i(k),\ k = 1, N_{win}$ and $\boldsymbol{x}_j = x_j(k),\ k = 1, N_{win}$, the Pearson correlation coefficient between country i and country j in a time window of N_{win} is defined as

$$\rho_{i,j} = \frac{\sum_{k=1}^{N_{win}} (x_i(k) - \overline{x_i})(x_j(k) - \overline{x_j})}{\sqrt{\sum_{k=1}^{N_{win}} (x_i(k) - \overline{x_i})^2 \sum_{k=1}^{N_{win}} (x_j(k) - \overline{x_j})^2}} \tag{2}$$

where $\bar{x}_i = 1/N_{win} \sum_{k=1}^{N_{win}} x_i(k)$. In our particular case, $\mathbf{x}_i$ corresponds to each of the dD_i time series so that $1 \le i \le 29$ (number of countries) and $1 \le k \le N_{win}$ (number of analysed quarters). To transform correlations, $\rho_{i,j}$, into distances, we follow Gower [35] and define the distance $d(i,j)$ between the evolution of the two time series $\mathbf{x}_i$ and $\mathbf{x}_j$ as

$$d(i,j) = \sqrt{\rho_{i,i} + \rho_{j,j} - 2\rho_{i,j}} = \sqrt{2(1-\rho_{i,j})}. \tag{3}$$

To examine the temporal behaviour of the interdependence relationships between the elements, we calculate the distance correlation matrices in windows of $N_{win} = 15$ quarters. Then, we move each temporal window over the entire sample period in one-quarter increment (overlapping windows) beginning at 2000. Hierarchical trees (HT) and MSTs [21,31] were calculated in each temporal window of fifteen quarters.

With the objective to evaluate the temporal changes of countries debt-to-GDP relations, two different clustering measures were used. On the one hand the agglomerative coefficient (AC) [36] was employed to infer how the debt-to-GDP hierarchical structure evolves over time. In each temporal window of fifteen quarters, the AC was calculated on the cor-

[4] Other correlation coefficients might be used, unless they are less employed. For instance, Gomez et al., [34] use over GDP data, the Kendall rank correlation. Supplementary Fig. S2 (see Appendix A) shows the equivalent of Fig. 2 by using the Kendall correlation.

responding HT, in such a way that an AC close to 1 implies a highly nested structure. On the other hand, the cophenetic correlation (CC) [37] between HT was calculated along the temporal windows. This measure provides an idea of how similar is the grouping structure in two different HT, such that a value of CC close to one implies a very similar grouping structure. As previously mentioned, in the supplementary text at the end of the paper, we provide some more details about the measures employed in this work.

2.2.2. Network analysis: Synchronization and community structure

As a complementary point of view we will use in addition another, yet related, methodology known as complex network [38]. By doing so we might be able to validate (or not) the results provided by the use of the HT approach. We calculate several of the most commonly used measures of complex network properties (see complementary text for a deeper explanation). For this purpose, we use the R package *igraph* [39].

To reduce the number of edges in the fully connected network provided by the correlation matrix, we require that the intensity of the links between countries to be at least[5] 0.52; i.e., an edge between countries i and j exists only if $abs(\rho) \geq 0.52$ in Eq. (2). Having defined the network nodes (countries) and the links between them (absolute value of correlations higher than 0.52), the connectivity or node *degree* of a particular node is defined as the number of links (connections) incident to that node. Nodes with high degree are highly connected with the rest of the network nodes.

Two important parameters in the network are the average path length (APL) and the density of links (DoL). Both were calculated in the whole 29-countries network for each temporal window of fifteen quarters (approximately 4 years). The APL was calculated as the average of all the shortest paths between every pair of vertices in the network, in terms of the number of steps along the nodes. In this sense, low values for the APL imply a highly connected topology. The DoL is the ratio of the actual number of edges in the network to the number of all possible edges between the network nodes. A network with many links or a high AC implies a highly synchronous behaviour. We also evaluate the community structures in the whole network. A commonly used community-detection algorithm involving the maximization of modularity was used [40]. Roughly speaking, modularity scores the fit of a proposed partition in a network with the community structure the network actually has. A value of the modularity close to one implies a strong community structure.

With the objective to evaluate whether co-movements in countries' debt-to-GDP ratios have a tendency to be clustered in particular groups of countries, the network assortativity (ASO) was evaluated in each temporal window. Given a particular characteristic of the networks nodes, as for instance, their degrees, the network ASO quantifies the tendency of nodes of equal degree (same number of connections) to be connected among them. A highly assortative network has an ASO close to 1. On the other side, a dissortative network has an ASO close to -1. In this sense, positive values of ASO imply that network nodes tend to be connected with nodes of similar number of connections. This definition, however, can be extended to other network nodes characteristics. In particular, we study the tendency of network nodes, i.e. countries' public debt-to-GDP levels, to be connected with other countries of similar percentage of debt. Table S1 at the supplementary information section summarizes our findings, organized by network measure. Also, in the supplementary text (see Appendix A) a brief description of these measures is provided.

3. Results

Fig. 2 shows four hierarchical trees corresponding to fifteen-quarter windows in different moments of our period sample, (A) 2002Q2–2005Q4, (B) 2002Q3–2006Q1, (C) 2005Q4–2009Q2, and (D) 2009Q3–2013Q1. All of them are built by using the dissimilarity matrix (3) and the commonly used average linkage clustering algorithm [41,42,20]. Fig. S1 displays the corresponding MSTs. As it is clearly seen, each of them presents differences in both clusters and overall structures. However, the two firsts (panels A and B) are fairly similar between them but completely different from the others. Two clear groups are observed in the two firsts HT. One of the groups contains, among others, France, Germany, Italy and Spain, and the other group includes United Kingdom, Portugal and Greece. Additionally, similar subgroups are observed in both of them. For instance, the group of Austria, Italy, Belgium, Ireland and Hungry is presented in both of them. Spain, Slovenia and Slovakia are in the same situation forming a group in both dendrograms as happens to United Kingdom and Finland or Greece and Romania. However, the existing similarities in these two dendrograms are destroyed when comparing with dendrograms in panels C and D, unless some countries continue to be pretty close from each other such as Italy, Belgium and Austria which implicates similar public debt-to-GDP evolution during the whole period under analysis.[6]

This figure uncovers important changes in the public debt network microstructure over time, especially when the intense period of turbulence around 2008 is included. In fact, as we shall show below, the financial crisis seems to break previous

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[5] A Shapiro–Wilk test was performed in every time series to evaluate their normality. In 87.97% of the cases (1050 time series) the test fails to reject the null hypothesis of normality ($p < 0.01$). For normal samples, the t-test yields a p-value < 0.05 when $\rho \geq 0.52$. We therefore set the threshold links in this value of 0.52 knowing that in most cases, the links are statistically significant. By fixing a single threshold value for all the cases, this procedure allows us to both speed up and simplify computations with no losses of robustness. In any case, the alternative approach of estimating the correlation statistical significance by using a bootstrapping technique is beyond the scope of the present work.

[6] Unless not presented here, these countries remain together in longer period networks. For instance, we calculate MST and HT for 2000Q1–2008Q2 and 2008Q3–2014Q1 periods and this same group is observed in both of them.

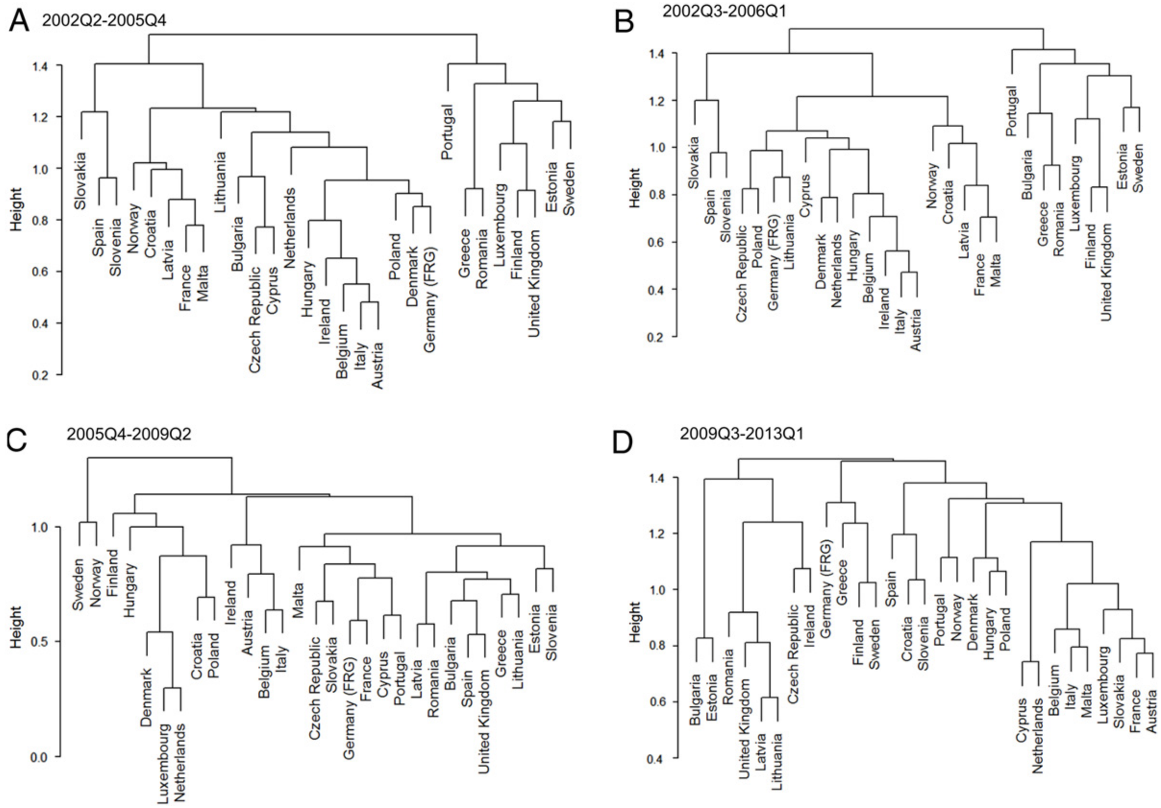

Fig. 2. Hierarchical trees in four different temporal windows (A) 2002Q2–2005Q4; (B) 2002Q3–2006Q1; (C) 2005Q4–2009Q2; (D) 2009Q3–2013Q1.

organization by creating emerging and different network structures. Fig. 3 (upper panel) depicts the CC for overlapping (one quarter step) windows of fifteen quarters. Only significant values ($p < 0.05$) of correlations were plotted. Non-significant values were considered as 0. As explained in the Method section, the dendrogram structure in every temporal window is compared, by means of the CC, with every other dendrogram in other temporal window, both forward and backward in time. Therefore, persistency over time in the clustering structure is analysed in this figure. Redder colours imply high correlation between hierarchical structures in two different dendrograms, while lighter colours imply low values of correlation. In this figure a disruption in the dendrogram clustering structures is observed starting at the period encompassing the quarters Q1 of 2005 to Q3 of 2008 including thus the burst of the financial crisis during 2008. The big turbulence at the end of 2008 produced a dramatic change in the way countries public debt was organized. It is apparent in the cophenetic graph that similarities between dendrograms are rather strong even in the cases of dendrograms separated by 5–6 years apart, during the first part and until the window 2005Q1–2008Q3. However, after that period things look quite different. The new structures in the hierarchical trees are of a very different kind to the previous ones. This is readily apparent in the lack of correlations between dendrograms in the periods subsequent to 2005Q1–2008Q3 with those dendrograms of previous periods to that quarter. Moreover, the whole structure of the cophenetic plot in the portion prior to 2008 is different from the structure after that year, implying a change in the internal dynamic of the public debt-to-GDP co-movement network.

With the objective of visualizing the evolution of the inner structure of dendrograms during the whole period we calculated the AC in each temporal window (Fig. 3, lower panel). Three clear regions can be observed in that figure. The first region encompasses approximately the years 2003–2007 during which the AC behaves in a stable fashion with a value around 0.4. The second region, starting approximately during the window 2005Q1–2008Q3 and ending at 2007Q1–2010Q3, is characterized by a fast rise and fall in the value of the AC, reaching values close to 0.5. The last region, from 2007Q1–2010Q3 to the end is characterized by a constant decline of the AC, with values as low as 0.3, implying thus a less nested structure. The dashed vertical line marks the window where an abrupt change in the CC appears, as commented above. The AC behaviour also displays an abrupt change at that particular period, increasing sharply its value. The combined information provided by both the CC and the AC shows a major change in the clustering structure of the HTs, due to a sharp jump after 2007. This change in the HT structure is towards a more nested structure, as reflected by the AC, during a period of approximately 8–10 quarters, to finally returns to previous and even less nested structures.[7]

[7] The selection of the HTs in the examples showed in Fig. 2 are in line with results provided by the CC and the AC. In fact, we have selected two HTs with just a quarter difference to show the clustering similar structure at the beginning of our time sample as Fig. 3 reveals.

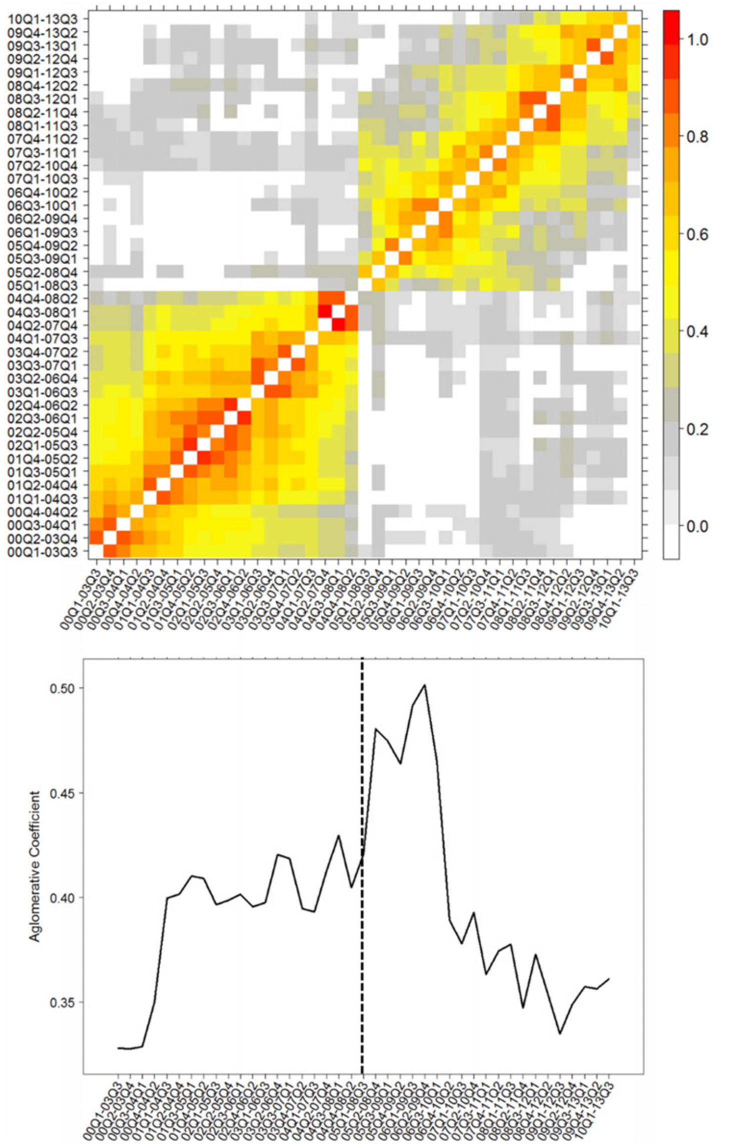

Fig. 3. CC (upper panel) and AC (lower panel). 15 quarters overlapping windows. 2000Q1–2014Q1.

To further analyse the disruption observed in Fig. 3, but from a different perspective, we calculate different measures of network properties. First of all, we have calculated the community structure in each temporal window, which is depicted in the upper panel of Fig. 4. Countries belonging to the same community are coloured identically. The maximum number of communities present in the whole period is 15, which occurs mainly in the first part of the graph (2002Q2–2003Q3) and in the last part (2011Q1–2012Q2). Large number of communities, as in the above cases, means that most of the countries form small communities (clusters) or are otherwise isolated (clusters of a unique element). On the other side, low number of communities, as for instance since 2007Q3 until 2009Q3, implies that most of the countries are tightly connected in a small number of communities.

Examples of the above community organization are depicted in the lower panel of Fig. 4, corresponding to windows 2002Q1–2005Q3 (left panel), 2005Q4–2009Q2 (centre panel) and 2009Q4–2013Q2 (right panel). In the first case there exists a big cluster of countries, in grey colour, composed of twelve countries and several minor communities and two isolated countries (Greece and Romania), forming a total of seven clusters. In the second case, corresponding to the highest turbulence period of the financial crisis, most of the countries belong to one of three big communities, besides Norway which appears isolated, conforming a total of four clusters. In the third case, it seems that the organization found in the first part of the analysed period is recovered but communities are even less connected and more disperse, with a total of thirteen clusters. Note that the colours in panels (B), (C) and (D) do not correspond with colours in panel (A). An equivalent plot is presented in Fig. S2 but using the Kendall correlation coefficient, instead of the Pearson, as the link strength estimation.

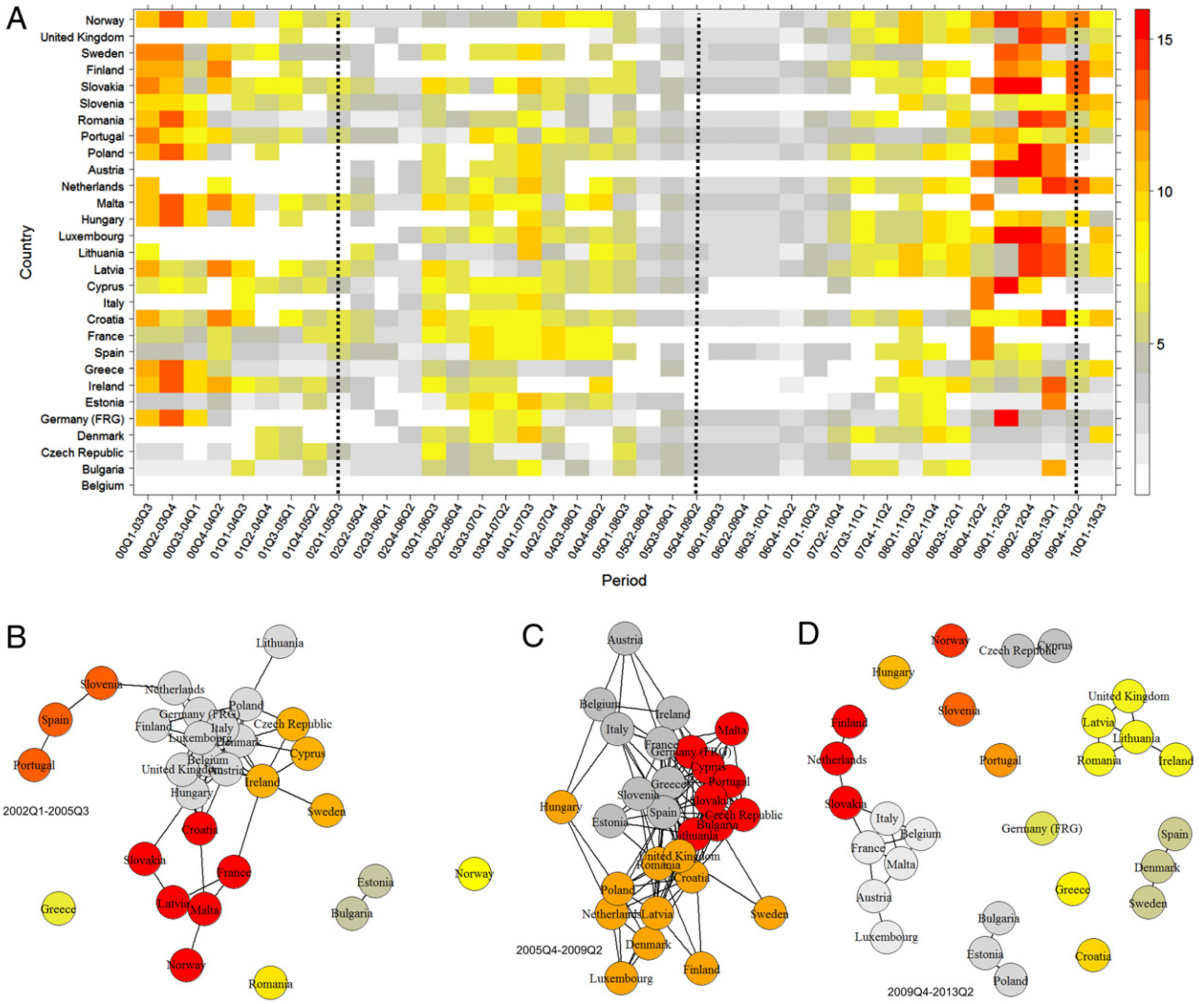

Fig. 4. Communities. 15 quarters overlapping windows. (A) Country community membership along 2000Q1–2014Q1. Vertical dashed lines mark different periods plotted in panels (B), (C) and (D). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

The above results are in accordance to findings represented in Fig. 2 and, moreover, shed new light regarding the public debt co-movements. The topological organization governing countries' relationships prior to 2007 is lost in the first quarters of that year. A stable and not-so-tight co-movement structure existing in the period 2002–2007 is abruptly changed in the first quarters of 2007, giving way to a period of tight co-movements in countries public debt, approximately until the year 2010. After that, it seems that the earlier organization is recovered, although with higher degree of freedom in the whole network, indicated mainly by the higher number of clusters and a declining AC.

Figs. 5 and 6 depict some measures of the complex system properties. Temporal evolution of node (country) degree is presented in Fig. 5. The highest node degree for most of the countries is observed during the financial crisis. Surprisingly, Spain, firstly, and United Kingdom, secondly, are the countries presenting the most intense connectivity in the network during the financial crisis, while Belgium, Austria, Estonia and Northern European countries (Finland, Sweden and Norway) are the less connected countries at this time. Interestingly, Belgium and Austria presented high connectivity before the crisis but this property is lost when the crisis hit the European economies. Fig. 6 shows the DoL, APL and the ASO (by degree) parameters. In line with previous properties of the network, a disruption in these parameters is observed at the time of the financial crisis. DoL parameter sharply increases at the beginning of the financial crisis but recovers low values and keeps them low afterwards. At the same time when DoL goes up, the APL parameter drops. However, this parameter observes sharp up and down jumps at the end of the period. Because most of the countries are isolated in this period, few links exist in the network and the APL is calculated only in the few formed sub-networks, thus artificially lowering the APL value.

Fig. 6 (bottom panel) also displays the ASO by degree in each temporal window. The ASO, in general, takes negative values when there is no tendency between nodes of similar characteristics (degree in this particular case) to be connected between them. On the other side, when an affinity of similar nodes to be connected between them exists, the ASO takes positive

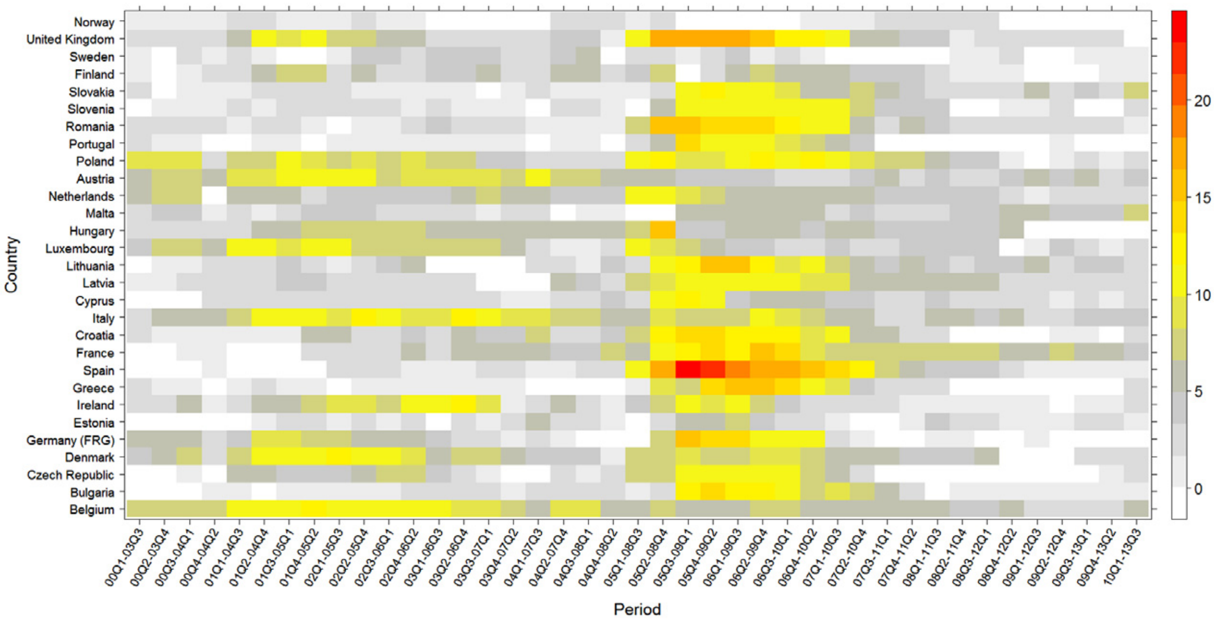

Fig. 5. Node degree by country. 15-quarters overlapping windows. 2000Q1–2014Q1.

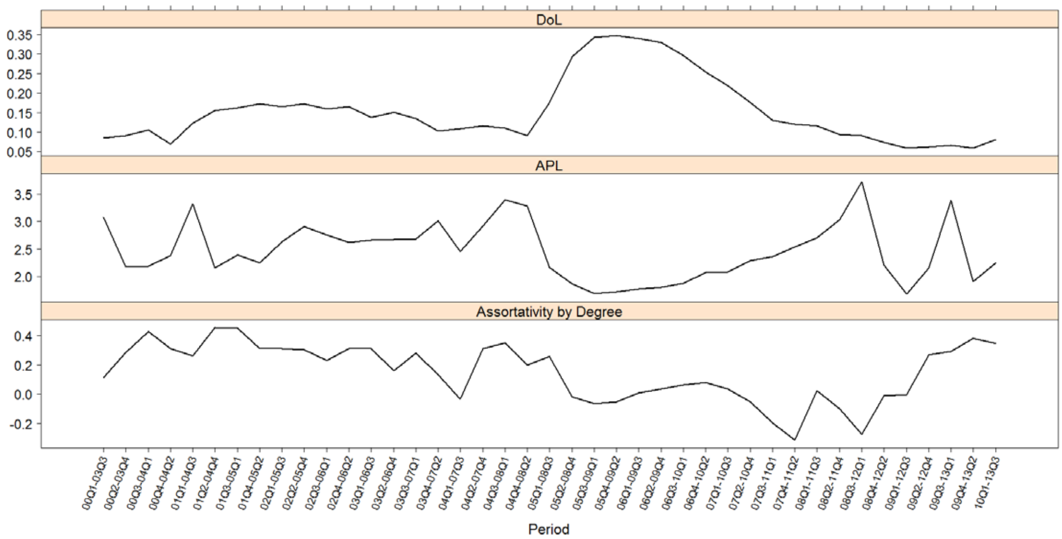

Fig. 6. Network parameters. (a) Density of Links; (b) Average Path Length; (c) Assortativity by degree. 2001Q1–2014Q1. See main text for explanation.

values. One can observe in that figure that until approximately the year 2008 a tendency exists of countries of equal number of links, i.e. equal degree, to be connected between them. However this tendency is lost since that year.

This finding leads us to ask whether the tight co-movements in the public debt during the financial crisis, as we have shown, were organized by other kind of ASO. To analyse it, we have calculated the ASO taking into account the level of public debt itself as the main node characteristic, instead of using the country degree, as we did before. The objective is to evaluate the degree of correlation between co-movements of public debt in countries with similar levels of it. To do so, we have implemented the following calculation: in each temporal window we have categorized each country being above or below a certain level of debt, i.e. 50%, 60%, 80%, etc. This procedure reduces the network to a bi-partite network, where each country belongs to one of the two categories, above or below the preset public debt ratio. In these bi-partite networks we have calculated the ASO measure. Because of public debts raised for most countries after 2008 and different debt histories are found around Europe, we repeat this procedure in each temporal window at different levels of debt-to-GDP, ranging

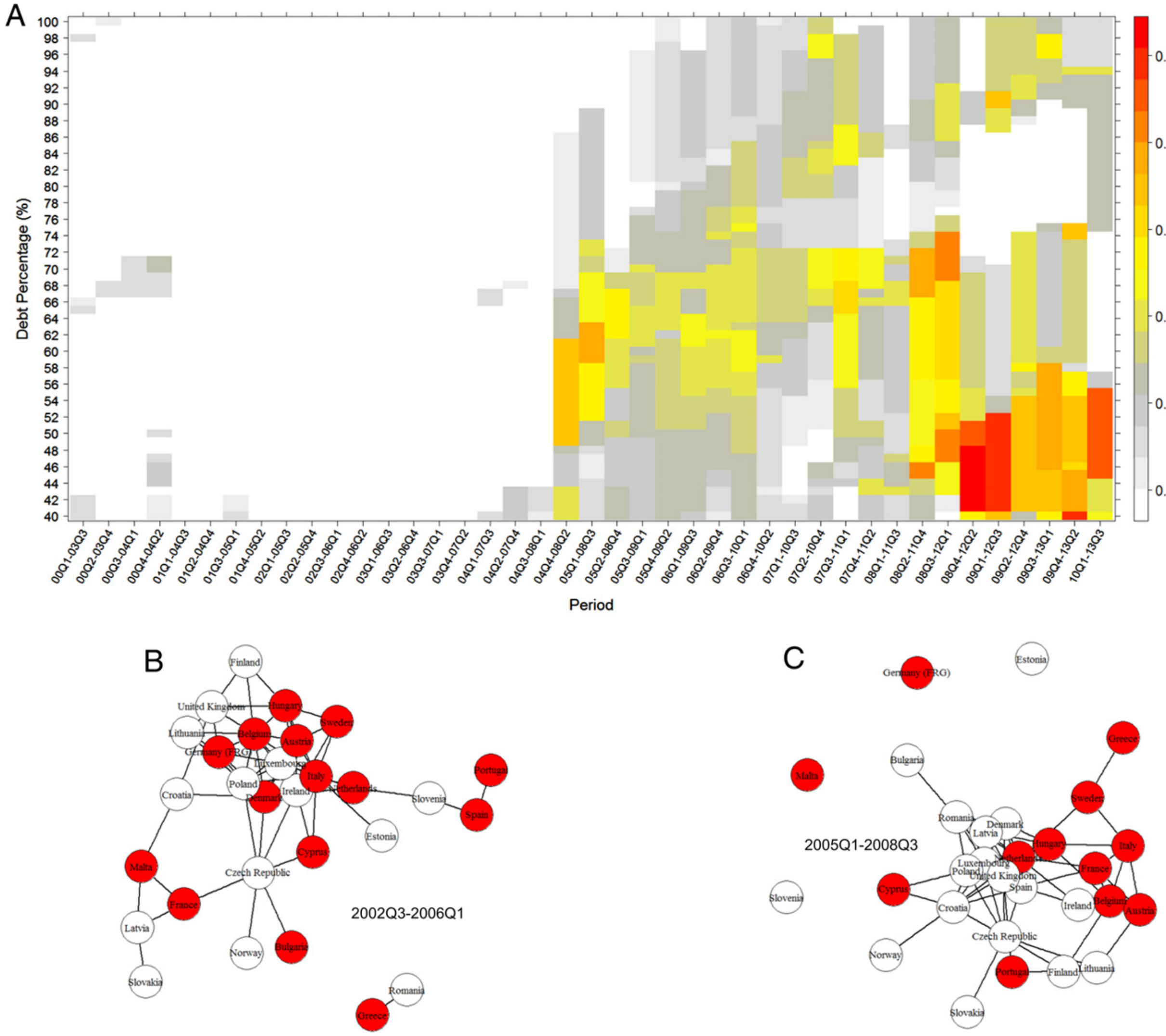

Fig. 7. ASO by public debt-to-GDP ratio, percentages. Fifteen-quarters overlapping windows. 2000Q1–2014Q1.

from 40% to 100% public debt. These results are plotted in the upper panel (A) of Fig. 7. Only positive values, assortative network, are plotted in colour. One can observe that, coincident with the crisis onset, countries of similar public debt, above or below a particular percentage, have also similar co-movements in its public debts. This characteristic, inexistent until the year 2006, shows up at that year and continues until the present.

As an illustrative example, we select 60% of the GDP as it is the limit of the stock of public debt established by the Stability and Growth Pact (Maastricht limit public debt) in two different temporal situations, depicted in panels (B) and (C) of Fig. 7. We have categorized countries accordingly whether their public debt is above (red) or below (white) the 60% of their own GDPs in the periods of evaluations 2002Q2–2006Q1 and 2005Q1–2008Q3. The respective networks are then plotted. Even though countries belonging to any of the two categories are the same in both situations, the network structure and, more important, the connectivity pattern is very different. In the first case, although a slight tendency between countries of similar debt to be attached between them exists, as for instance, Cyprus, Italy, Hungary, Belgium, Austria, Sweden, etc. the connections are also mixed up with countries owned public debt ratios below 60%. On the other hand, during the period 2005Q1–2008Q3, this tendency between countries of similar public debt to be connected between them is even stronger. As an example, during the first period, Czech Republic, a "white" country during both periods, have similar number of links with "red" and "white" countries, during the first period (panel B of Fig. 7). However, during the second period, panel C of Fig. 7, Czech Republic have many more links with "white" countries than with "red" ones.

Then, the disruption in the network organization previously observed coincides with the emergence of the level of public debt itself as a main driver for explaining the new clustering organization.

4. Conclusions

In this work we have followed the analysis of the public debt hierarchical structures formerly carried out by Kantar et al. [20] and Dias [19,18]. They have shown, by using clustering techniques as the MST, that two groups of countries, more and less affected, are formed as a consequence of the debt crisis. Moreover, these groups tend to separate one from each other as the crisis deepens. Here, we have zoomed into the temporal changes of the debt-to-GDP ratios during the period 2000–2014 by using short temporal windows of nearly 4 years, with the objective of studying the European public debt network evolution from 2000.

From this analysis we observe a sharp increase in synchronization and connectivity of the public debt-to-GDP ratio during the global crisis, in line with similar analysis applied to stock markets [13,14,43]. As a consequence, a disruption in the previous stable structure is observed, as the CCs shows. Therefore, topology and structural arrangements of the network dramatically change over time mainly triggered by the economic shock. Analysis for longer periods such as that presented by Kantar et al. [20] tends to omit this structural transformation. Note that as far as the GDP data allows, only a coarse-grained evolution can be inferred from this kind of analysis.

From a community structure perspective, we observe during this period of economic and financial turbulence a sharp drop in the number of communities that were observed in the network structure before the crisis. Moreover, the network transforms into a more centralized one, in the same fashion as other similar studies applied to stock markets have shown (e.g., Refs. [24,44]). However, as the crisis evolves, the number of communities increases being the highest at the end of the period under analysis. As seen in Figs. 4 and 5, unless connectivity at the end of the period is very low the high number of communities are far from each other revealing no permanency in tight groups in terms of their dynamics (part (c), Fig. 4). These results contrast with the analysis applied to daily government yield rates presented by Dias [19,18] as his findings show two different and somehow permanent groups that separate from each other as the European public debt crisis move forward.

Our results show an intense diversity in the number of communities and low both connectivity and synchronicity at the end of the period. However, we also have shown that extreme events quickly turn this diversity into a more connected and centred structure with potential contagion effects to other countries. Additionally, a new pattern of country public debt-to-GDP dynamic seems to emerge directly related to the public level itself. Further analysis however must be done to analyse other potential variables driving the new emergence of clustering after the financial crisis.

To sum up, our findings show high synchronicity and connectivity and the lowest number of communities at the time of the crisis. Additionally, we observe less diversification and a more centralized network topology at that time. Finally, the financial crisis triggered a new network organization which is arranged by public debt levels itself.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at http://dx.doi.org/10.1016/j.physa.2015.05.052.

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