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Sensitivity and vulnerability of European countries in time of crisis based on a new approach to data clustering and curvilinear analysis

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Abstract: *In this paper we inquire into the way the global crisis during the period 2008-2012 reflected in some macroeconomic and social indicators of the EU member states. Applying Curvilinear Component Analysis (CCA) on a dataset representing these social indicators, a classification of EU countries is obtained. Comparing this classification with the one resulted from a previous study with self organizing maps (SOM) it was noticed that the clusters are almost identical, CCA having the advantage of dimensionality reduction over SOM. CCA shows the detailed distances between the countries/year, dismissing outliers. This allows for a case by case study both in terms of clustering and in terms of temporal analysis. The research findings prove the sensitivity and vulnerability of European countries during the crisis and could help the policy makers to identify effective measures for strengthening the protective capacity of their states in the event of a future economic and social crisis.*

Keywords: *curvilinear component analysis, dimensionality reduction methods, data clustering, visualization.*

JEL**:** *F53, H75, L32, M41.*

Introduction

This paper addresses the impact of the global crisis on economic and social development of the EU member states in the period 2008-2012. Major changes generated equally by this global phenomenon, but also domestic and European policies are reflected in macroeconomic and social indicators that will be the basis for the analysis in this paper.

The main reason we addressed this issue is an interesting paradox consisting of various economic and social effects of the crisis and government measures in the analysed period. The crisis period is influencing both the economic

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indicators and the life standard of the citizens (Lazaroiu, 2015a) and their health (Lazaroiu, 2015b).

The Curvilinear Component Analysis (CCA) is a new effective method for the unfolding and representation of high-dimensional nonlinear data sets (Demartines, 1996).

With CCA we will prove and view these effects. In addition, CCA helps us group the states into clusters and explain the dynamics of positions occupied by some states in relation to the others. Thus, we will see the effectiveness of domestic and European policies in each state during the crisis period (Nica, 2015a).

The paper is organized as follows. Section 2 discusses the impact of the financial crisis on the economy of the EU and the measures undertaken by the European Systems Risk Council to detect the risks of the European financial system. Section 3 describes the Curvilinear Component Analysis, a clustering method which lies at the basis of the software we use. Section 4 contains a description of the data set and an analysis of the countries grouped in 6 clusters.

The results obtained by CCA are compared with those derived from a previous paper (Androniceanu and Georgescu, 2013), where SOM was used for data clustering. The paper ends with conclusions.

1. The crisis context

The financial crisis that hit the global economy since the summer of 2007 is without precedent in post-war economic history. Although its size and extent are exceptional, the crisis has many features in common with similar financial-stress driven recession episodes in the past. The crisis was preceded by a long period of rapid credit growth, low risk premiums, abundant availability of liquidity, strong leveraging, soaring asset prices and the development of bubbles in the real estate sector. (IMF, 2012)

The current global crisis has demonstrated the importance of understanding sources of domestic and global vulnerabilities that could lead to a systematic event (Popescu et al., 2016). The crisis in Europe shows that market economies are still susceptible to collapse or near-collapse from financial crisis. The financial crisis has had a pervasive impact on the real economy of the EU, and this in turn led to adverse feedback effects on loan books, asset valuations and credit supply (Snower, 2012).

The financial crisis strongly affected the EU economy through three essential transmission channels: (1) via the connections within the financial system itself; (2) via wealth and confidence effects on demand; (3) via global trade that collapsed in the final quarter of 2008 as business investment and demand for consumer durables (Roeger, Veld, 2009). Some EU countries have been more vulnerable than others, reflecting inter alia differences in current account positions, exposure to real estate bubbles or the presence of a large financial centre. Such differences have been identified and analyzed in this paper by using SOM and CCA methods (Collan et al., 2007).

The crisis in Europe has had so far very different consequences in different countries. The export-oriented economies were strongly affected by the recession of 2008-2009. They relied on exports and world trade collapsed in autumn 2008 by some 20 per cent (Roeger, Veld, 2009). In 2009 Germany and Japan had worse recessions than the USA, but they were quick to recover thereafter. Unlike the debt-led economies, they were not burdened by high household debt and shrinking property markets.

The USA had a weak recovery (with unemployment still at twice the pre-crisis level), Germany (as well as Austria and the Nordic countries) experienced a speedy bounce back, whereas a deepening of the crisis took place in the peripheral European countries. (Gorton, 2012).

In Ireland and in Spain there was a property bubble that had burst, leaving households with a huge debt burden and banks with losses (due to mortgage defaults and failure of construction firms).

Greece was the first country to experience a sovereign debt crisis – that is, the government was unable to raise funds on private financial markets at sustainable interest rates (Sarlin, Peltonen, 2011). Countries have not only to finance their net deficits; they also have to roll over those parts of the debt that matures. Public debt is much higher, say 100 per cent of GDP. This latter part is typically larger than the former (Gaspar, Schinasi, 2009).

As can be seen in recent years, Germany has dominated European economic policy. It has dictated the conditions of the Greek rescue package and it is blocking the issuance of euro bonds or other steps towards fiscal integration. Historically, the European monetary union (EMU) was to a large extent designed by Germany and France. But the very fact of EMU, namely the introduction of the euro, was not a German initiative; it was the other European countries that wanted a common currency and Germany was reluctant to agree.

As is known, it was a French condition for accepting German unification (Smits, Woltjer, 2009). We can see that the real challenge is in the field of politics, not economic theory. European state structures are creations of capital, in part designed to circumvent national political processes (Burlacu, 2015).

In the last six years, since the global crisis has become more visible in Europe, most EU policy efforts so far have focused on crisis control and mitigation, which are important, but the reality is proving the fact that this is not enough In this paper are explored the effects of the European governments policies to their countries and how effective their measures in time were. Public administration is playing a key role in time of crisis (Nica, 2015b)

The current situation of the EU member states is demonstrating the fact that the framework for financial crisis prevention that was in place prior to the crisis proved underdeveloped. The crisis has demonstrated how important is to have an effective and functional coordination and monitoring mechanism in

Europe. That mechanism is influencing the social network (Popescu, 2015a). As a consequence, the European Commission designed a new framework for safeguarding financial stability in EU member states (figure 1).

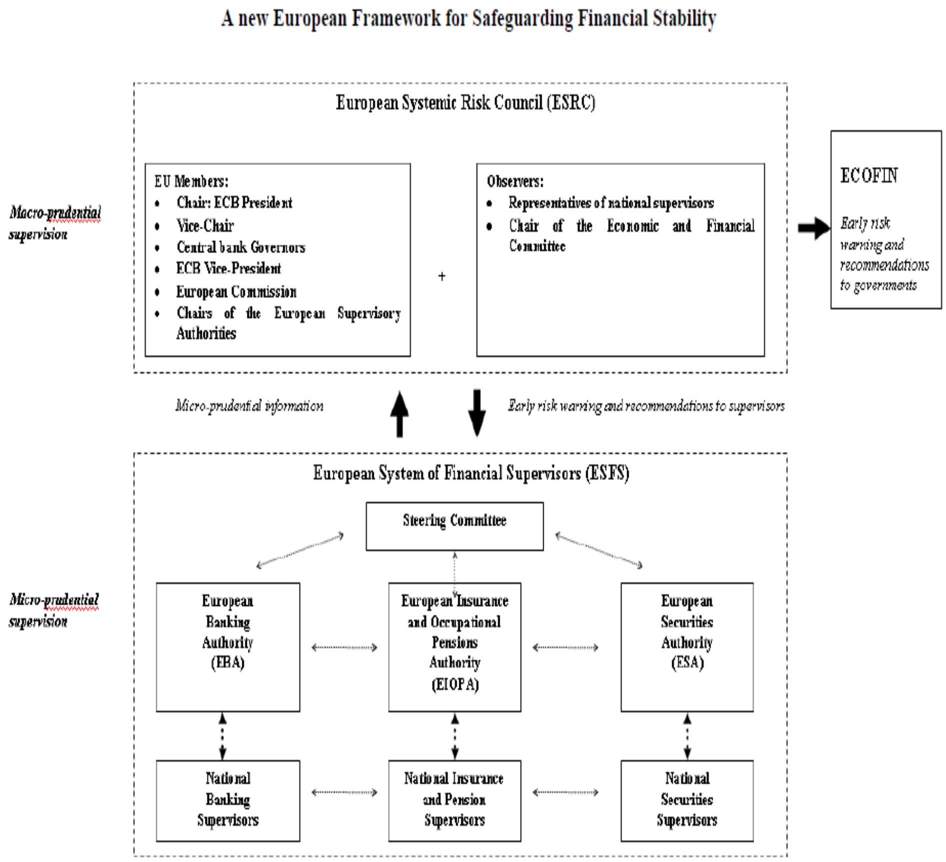

Figure 1. European Systemic Risk Council (ESRC)
(Source: Snower, 2009)

Nowadays, such mechanism is becoming necessary in order to act in the following three directions simultaneously: *crises prevention* for avoiding the crisis escalation and deepening*; crisis control* for minimizing the damage by preventing systematic defaults and *crisis resolution* to bring crisis to a lasting close and at the lowest possible cost for the citizens and the European business community (European economy, 2009).

As the EU Commission explained, the roles of ESRC (European economy, 2009) were defined as follows:

- collect and analyse all information relevant for monitoring and assessing potential threats to financial stability that arise from macro-

economic developments and developments within the financial system as a whole;
- identify and prioritize such risks;
- issue risk warnings where risks appear to be significant;
- give recommendations on the measures to be taken in reaction to the risks identified;
- monitor the required follow-up to warnings and recommendations, and liaise effectively with the IMF, the FSB and third country counterparts.

The analysis of the European economies in time of crisis highlights the fact that the euro area is strongly linked with the global economy and existing imbalances (Balcerzak, 2016). Thus, while the euro area as a whole has not in this sense contributed to global imbalances, the resolution of these imbalances will likely affect it heavily (Aizenman, Sun, 2008). This underscores the need to step-up euro-area involvement in global affairs (Obstfeld, Taylor, 2003).

2. Data clustering method

Within the field of Data Clustering for classification we find an array of methods, often different in the way they operate, yet all falling in either the supervised or the unsupervised category. Supervised methods position patterns according to the multidimensional information of its attributes, but have an extra field for the class of each pattern, that will be used to train data in order to classify new incoming data. Unsupervised methods cluster data according to its attributes alone. In unsupervised methods, classes are decided a posteriori, and not according to a pre-existing class field. The first and most commonly used methods include Principal Component Analysis (PCA) (Jackson, 1991, Jolliffe, 2005), its regression-based counterpart called Factor Analysis (FA) (Reinhart and Rogoff, 2008, Child, 2006, Zientek, 2008) the more recent Independent Component Analysis (ICA) (Comon, 1994, Hyvarinen and Oja, 2000), or the multidimensional projection selector called Projection Pursuit (PP) (Friedman and Tukey, 1974, Friedman and Stuetzle, 1981, Huber, 1985, Friedman, 1987). ICA works particularly well when a hypothesis of independent attributes turns out to be correct (Popescu, 2015b).All the others aim for the right combination of attributes, accepting interdependencies. However, these methods detect only linear dependencies within the input data.

Non-linear dimensionality reduction methods (NLDRM) take into account different forms of non-linear dependencies amongst attributes, allowing for a more comprehensible unfolding of data in the projected space. One of the first NLDRM to be published and commonly used is the Sammon Projection or Sammon Mapping (SM) (Sammon, 1969, Dybowski et al., 1996, De Ridder and Duin, 1997, Lerner et al., 2000).

It is based on the preservation of the distances of the initial n-dimensional space. Let d^*_{ij} be the actual Euclidean distance between patterns i and j, and let d_{ij} be the distance once a certain projection has been made. The aim of a good SM is to minimize:

$$E = \frac{1}{\sum_{i<j} d^*_{ij}} \sum_{i<j} \frac{(d^*_{ij} - d_{ij})^2}{d^*_{ij}} \qquad (1)$$

The original SM article uses a steepest descent procedure to optimize an initially random set of projected patterns. Other methods such as Genetic Algorithms (Pohlheim, 1999, Edwards and Engelbrecht, 2006), Simulated Annealing (Klein and Dubes, 1989, Xinzhi Li, 2004), Particle Swarm Optimization (Figueroa et al., 2005, Edwards et al., 2005, Edwards and Engelbrecht, 2006) or other Gradient Descents (De Ridder and Duin, 1997, De Backer et al., 1998) have been proposed over initially random projections. An attempt to accelerate the transition from the initial state to the optimized one is to begin the optimization process with the first Principal Components (Lerner et al., 2000).

There are other methods for dimensional reduction such as Principal Curves and Surfaces (Hattie 1984), Manifold alignment (Wang and Mahadevan, 2008, Wang and Mahadevan, 2009), or Kernel PCAs (Scholkopf et al., 1999), but SM is relevant to Curvilinear Component Analysis (CCA) (Demartines and Herault 1995, Demartines and Herault, 1997) because both are based on projections where the distances between patterns are preserved. CCA improves SM. SM cannot reproduce all distances; CCA tries to reproduce first short distances, then long distances.

In CCA, preserving the notation used above, the cost function proposed is:

$$E = \frac{1}{2} \sum_{i} \sum_{j \neq i} (d^*_{ij} - d_{ij})^2 F(d_{ij}, \lambda_y) \qquad (2)$$

where

$$F(d_{ij}, \lambda_y) = \begin{cases} 1 & \text{if } d_{ij} \leq \lambda_y \\ 0 & \text{if } d_{ij} > \lambda_y \end{cases}$$

During the minimization of the cost function, λ_y can evolve over time, or be manually controlled by the user in a more interactive work scheme. Just as it happened with SM, CCA has been tried with different heuristics for the minimization of the error or cost function. A popular upgrade to CCA is Curvilinear Distance Analysis (CDA) (Lee et al. 2000). In CDA, geodesic (and not Euclidean) distances are preserved. This can be an advantage when complex topologies are added to the difficulty of a multidimensional setting. However, it is important to indicate that although CDA can often be the most indicated for classification, part of topology-related information will not be reflected in the projection.

For the classification purposes of this article, CCA provides satisfactory results. According to (Demartines and Hérault, 1997), CCA enhances SOM and other algorithms (SM, multidimensional scaling) by using a new cost function, speed, and interactivity as a result of the speed.

3. Main results

3.1 Dataset information

The dataset was collected from Eurostat and it comprised yearly indicators for 2008-2011 for 27 countries from the European Union (EU). The structure of the group of countries involved in our research are presented in table 1.

Table 1. List of countries included in CCA

Belgium	Spain	Malta	Finland
Bulgaria	France	Netherlands	Sweden
Czech Republic	Italy	Austria	United Kingdom
Denmark	Cyprus	Poland	Iceland
Germany	Latvia	Portugal	Norway
Estonia	Lithuania	Romania	Switzerland
Ireland	Luxembourg	Slovenia	
Greece	Hungary	Slovakia	

Eight variables were chosen to explore and visualize the development of the EU countries during 2008-2011: Gross Domestic Product per Capita, Export and Import, Final Consumption, Income Saving and Net Lending, Government Deficit and Debt, Exchange Rate, Purchasing Power Parities, EU Direct Investment. Overall the set of data consisted of 108 rows, 27 countries with 8 variables for each row. In 2013, we used SOM to study the clustering of the EU-member states depending on the macroeconomic variables from above during financial world crisis during 2008-2011. Similar studies were done in (Collan et al., 2007), (Sarlin et al., 2012), (Sarlin, 2013) where SOM was used in analysing and visualizing the changes of some macroeconomic indicators of the EU member states since the global crises began. By applying CCA, the 108 rows were grouped into 6 clusters according to their similarities (Figure 2). The axis in Figure 2 are a nonlinear combination of all the attributes in the dataset. Certain attributes grow according to certain directions in the graph. But what really matters is the relative distance between each dot. The outliers are a result of small neighbourhood. The 6 clusters have the colours: dark red, light red, green, yellow, dark blue and light blue. We survey the content of each cluster and make a comparison with the results given by SOM on the same dataset (Androniceanu and Georgescu, 2013). We notice that the characteristics of the clusters obtained with CCA are almost identical with those resulted from SOM.

Dark blue cluster (similar to **Cluster 1** from (Androniceanu and Georgescu, 2013)).

In this cluster mainly economies of developed countries of the European Union between 2010 and 2011 stand out.

Green cluster (similar to **Cluster 3** from (Androniceanu and Georgescu, 2013)).

This cluster comprises stable Western European countries such as Great Britain, Germany, France, Italy, Austria, France, Netherlands, Belgium in 2008, 2009 but also the Nordic countries Sweden, Finland and Denmark during 2008, 2009.

Yellow cluster ((similar to **Cluster 4** from (Androniceanu and Georgescu, 2013)).

This cluster contains in totality East European countries such as: Lithuania (2008-2011), Czech Republic (2008-2011), Poland (2008, 2010), Slovakia (2008-2011). Czech Republic and Slovakia have the highest GDP per capita in this group.

Light blue cluster ((similar to **Cluster 2** from (Androniceanu and Georgescu, 2013))

This cluster is characterized by developing countries where Bulgaria (2008-2011), Poland (2009), Estonia (2008-2011), Slovenia (2008, 2009) stand out. Also Malta (2008-2010) and Latvia (2008) are elements of this group.

▪ **Light red cluster**

▪ This cluster comprises only one country, Luxembourg and is similar to Cluster 5 from (Androniceanu and Georgescu, 2013).

Luxembourg has a special position, mainly because of its effective government measures during 2008-2011. It generates several advantages accumulated in time. Some of them are presented and explained here.

First, the industrial sector, initially dominated by steel, has become increasingly diversified and gave to the national economy a high degree of economic flexibility. Following strong expansion from 2004 to 2007, Luxembourg's economy grew by 3.6% in 2009, but rebounded in 2010-2011. The country continues to enjoy an extraordinarily high standard of living - GDP per capita ranks among the highest in the world, and is the highest in the Euro zone. Turmoil in the world financial markets and lower global demand during 2008-2009 prompted the government to inject capital into the banking sector and implement stimulus measures to boost the economy. So, the country had the capacity to reduce the negative influence of the international economic environment dominated by crises.

Secondly, this small, stable, high-income economy benefited from its proximity to France, Belgium, and Germany. These countries showed a good level of resistance in time of crises. This is all the more significant in that Germany is

Luxembourg's principal economic and commercial partner. Luxembourg has historically featured solid growth, low inflation, and low unemployment.

Thirdly, even if the economy of Luxembourg depends on foreign and cross-border workers for about 60% of its labour force, the unemployment has trended below the EU average. Government stimulus measures and support for the banking sector, however, led to a 5% government budget deficit in 2009.

Nevertheless, the deficit was cut to 1.1% in 2011. Even during the financial crisis and recovery, Luxembourg retained the highest current account surplus as a share of GDP in the euro zone, owing largely to its strength in financial services (Valter et.all, 2016). Public debt remains among the lowest of the region although it has more than doubled since 2008 as percentage of GDP.

Dark red cluster (similar to **Cluster 6** from (Androniceanu and Georgescu, 2013)).

This cluster comprises only one country, Hungary, during 2008-2011.

Hungary is also an exception in our clustering analysis, mainly because of its approach related to the global crises. Hungary has made the transition from a centrally planned economy to a market economy, with a per capita income nearly two-thirds from that of the EU-25 average. According to the published data, the private sector accounts more than 80% of GDP. Foreign ownership of and investment in Hungarian firms are widespread, with cumulative foreign direct investment worth more than $70 billion. The global economic downturn, declining exports, and low domestic consumption and fixed asset accumulation, dampened by government austerity measures, resulted in an economic contraction of 6.8% in 2009. In 2010, the new government implemented a number of measures including cutting business and personal income taxes, but imposed "crisis taxes" on financial institutions, energy and telecom companies, and retailers. The economy began to recover in 2010 with a big boost from exports, especially to Germany, and achieved growth of approximately 1.4% in 2011. At the end of 2011 the government turned to the IMF and the EU to obtain a new loan for foreign currency debt and bond obligations in 2012 and beyond. As we know, the EU also launched an Excessive Deficit Procedure to Hungary and requested that the government outline measures to sustainably reduce the budget deficit to under 3% of GDP. Unemployment remained high, at nearly 11% in 2011. Ongoing economic weakness in Western Europe is likely to further constrain growth in 2012. The discussion above is concentrated in the following table 2.

Table 2. Cluster characteristics

Cluster	Characteristics (examples of countries)
Dark blue cluster	mainly economies of developed countries during 2010-2011
Green cluster	stable Western European countries and Nordic countries (Sweden, Finland Denmark) during 2008-2009
Yellow cluster	East European countries

Cluster	Characteristics (examples of countries)
Light blue cluster	East European countries, Malta, Latvia
Light red cluster	Luxembourg (GDP per capita ranks among the highest in Europe, solid growth, low inflation, and low unemployment)
Dark red cluster	Hungary (a per capita income nearly two-thirds from that of the EU-25 average, cumulative foreign direct investment worth more than $70 billion, 1.4% growth in 2011)

3.2 CCA analysis

Androniceanu and Georgescu, 2013 already showed a reliable clustering in terms of the classes then proposed, also used here. CCA confirms the validity of these classes, as clustering is, for the most part, just as reliable (see Figure 2).

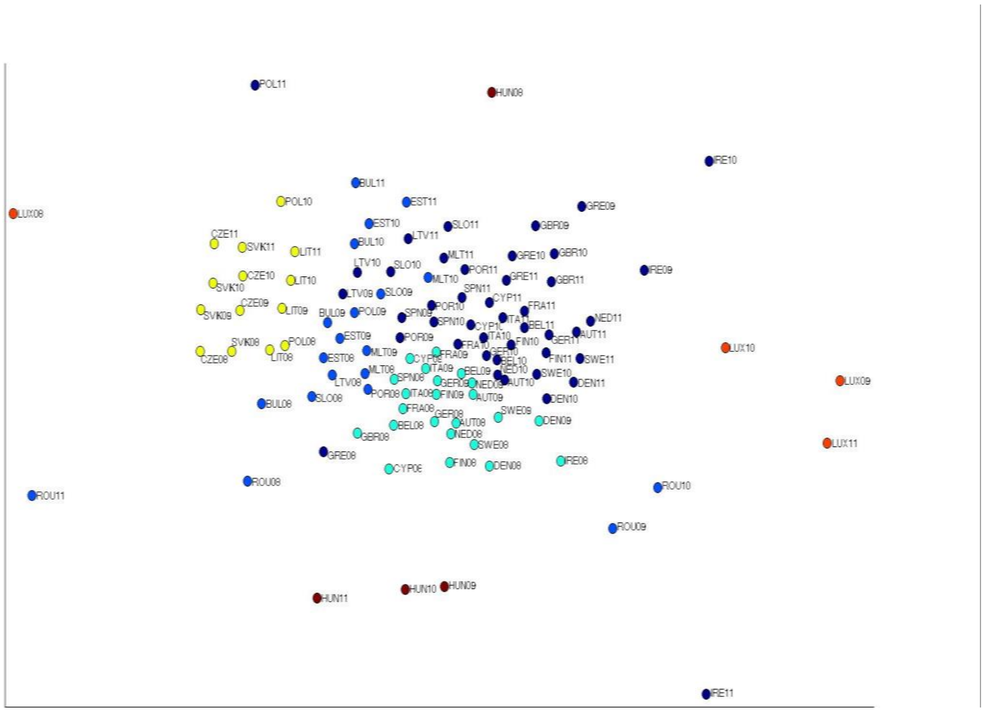

Figure 2. (Colour online) Clusters obtained by CCA

In the effort to preserve distances, first for the closest patterns, then for the others, CCA shows clear outliers. These patterns scatter around the main cluster in an apparent random fashion. They are not completely random in that those who are close to each other do preserve higher dimension distances (e.g. HUN09,10, and

11, or LUX09, 10, and 11, or ROU09 and 10). Their location around the main cluster is less relevant, since they have not been pushed by the constraint in (2).

Thus, what needs to be said about these countries is that their socio-economic history according to the attributes presented is unrelated to those in the other countries. In outlier countries where years are scattered, (like Rou, Ire...), CCA shows that their instability is much greater. They don't follow the main trend of the general cluster, nor their cluster, year by year, to themselves, showing at least some degree of local stability.

The remaining countries in the main cluster, show the degree to which the classification proposed in Androniceanu and Georgescu, 2013. Countries like Poland, that change, as years pass, from the Eastern Europe yellow cluster to the dark blue set, are well represented by CCA.

There is a certain overlapping between light blue and dark blue patterns. The last two years of Bulgaria and Estonia are closer to the last two years of Latvia and Slovenia. The CCA projection suggests two sub clusters for these countries: one for 08-09 and another for 10-11.

The rest of the main cluster is fairly consistent with the colour groups proposed. A geographical pattern seems to be on display also: neighbouring countries tend to have similar states, sometimes even as the years pass. This temporal evolution can be seen in greater detail in Figure 3. The 2008-2011 period is a transient state for all of Europe.

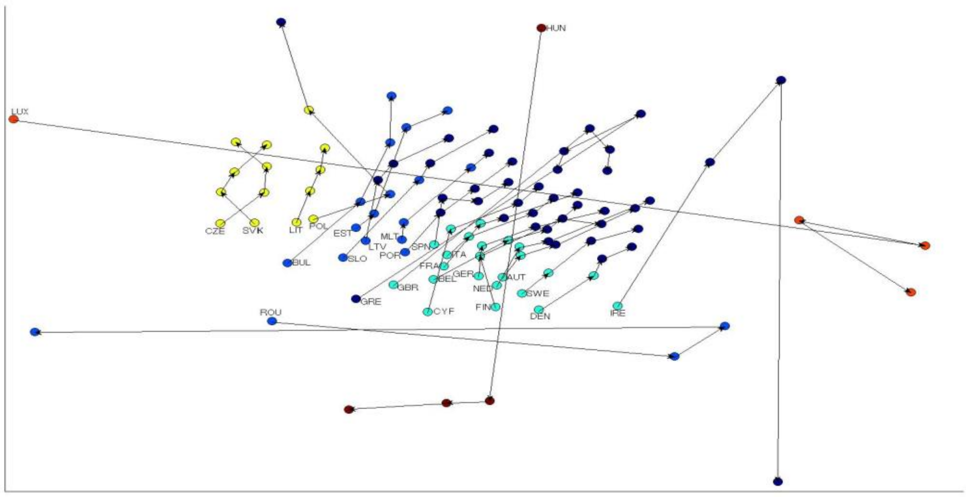

Figure 3. (Colour online) Temporal drive of the countries in the CCA results

Regardless of wealth and stability, all countries drift. While the axes on a CCA plot are a nonlinear combination of all the attributes, the arrow of time is clear in this plot. Yet we must not forget that it also implies the temporal drift of common macroeconomic standards. There are no cycles in this plot. There are no static economies. The attractor of most of these trajectories should be found at the true economic end of this crisis, maybe in the few years to come from now.

Figure 3 shows expected intertwined trajectories, i.e. countries that follow the general macroeconomic trend (the common direction of time), and do so with very similar trajectories. Amongst these countries we have {CZE,SVK}, {LTV,SLO}, {SPN,POR}, {FRA,ITA}, {BEL,FIN}, {NED,AUT}, and less remarkably {SWE,DEN} {SLO,MLT}.

There are also countries that follow the main trend, but do so close to countries not so expected. Such is the case of {GRE,GBR}, that for obvious reasons don't seem to have had a similar history in the period studies. Some economies are unexpectedly intertwined due to the difference in size they have, for example {BEL,FIN,GER}. All data is normalized using multivariate standardization, to avoid large economies to become outliers. However, larger economies are expected to be differentiated from smaller ones.

Conclusions

The work done by Androniceanu and Georgescu, 2013 has been extended using the Curvilinear Component Analysis data clustering supervised method. Clustering of the groups proposed is therefore confirmed by SOM (in the previous work) and CCA (here). Countries with unrelated socio-economic histories are singled out as outliers of the CCA output. The stability of their economic history is also put to question, due to the scattering in the results.CCA also shows the trajectories in time of the drifting economies, indicating that the time studied is a transient within the framework of the economic crisis. Overall, the data presented shows a very consistent set of nations, and allows for predictions on the years immediately after the interval studied.

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