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DO SOVEREIGN BOND SPREADS IN EU CONVERGE? AN ANALYSIS THROUGH SELF-ORGANIZING MAPS

Abstract. *This paper presents an empirical analysis related to sovereign bond spreads evolution since 1999 to 2011. Applying self- organizing maps, we find different groups of countries along the years related with their bond spreads variations. Moreover, we detect the euro effect and consider different groups of countries to the study. The financial crisis impact is also considered and shows interesting results.*

Keywords*: Self-organizing maps, financial crisis, sovereign bond spreads, eurozone.*

JEL classification: G01, C45, H63

1. Introduction

The EMU (European Monetary Union) is one of the most important policies applied to fully integrate the financial market. In the first two years after the introduction of the euro there was a general harmonization in the time series of the euro area bond market. It should be noted that the European countries that did not belong to the single currency, like United Kingdom, also increased their bond yield correlation with the countries that had adopted the euro (Martinez and Terceño, 2012). At the beginning of the EMU until the first half of 2008, bond yields of EMU sovereign debt had commonly been relatively close (Attinasi et al., 2009; Bernoth and Erdogan, 2012). The decrease of the bond spreads is mainly reflected by the introduction of the euro and the removal of the exchange rate risk.

Financial crises are changes in the financial system that produce collapses or severe disruptions that hinder the normal development of the economy. There are different concepts of this term and diverse channels by which they are transmitted to other economies, among which the so-called financial contagion effect.

Since the start of the recent financial crisis, in September 2008, most of European countries have been affected in many economic and financial aspects. The sovereign bonds spreads relative to Germany have increased markedly.

In our work, we analyze the sovereign bond spreads evolution of sixteen European countries. The aim of this paper is to analyze the bond spreads evolution from 1999 to 2011, i.e. since the period previous to the official currency circulation in the European countries until the crisis period. In particular, we are interested in studying the impact of the common currency and the financial crisis on the spread dynamics.

To fulfill the purpose of the article, self-organizing maps (SOM) are applied in order to identify different groups of countries in several subperiods according to spreads similarities.

SOM are especially suited for clustering tasks, since this kind of networks gathers elements according to their homogeneity considering all the attributes or variables defined by the researcher. One key advantage of this network is its unsupervised learning process that makes not necessary to define *a priori* groups. Groups are determined according to the similarities and differences of the elements considering all variables that form the patterns. SOM reduce the dimension of the input information (patterns are *n*-dimensional) to a bi-dimensional map. This kind of map reduces the complexity of dealing with *n* variables to a graphical interpretation. The planar location of the elements in the map keeps relation with the values of the *n* variables considered.

Given that the main objective is to analyze country spreads movements through the years, patterns are defined as a 12 dimensional 'country-year' vector where elements represent the annualized spread and the monthly spread variation.

The correlation among monthly sovereign bonds spreads changes is low. Consequently, in order to perform our analysis, it is essential to apply a methodology that considers jointly all spreads values that define a pattern and group those with greater similarities. In this sense, SOM are a useful tool for our purpose because they allow grouping into classes. Furthermore, it is not necessary to define classes beforehand and considers all spreads evolutions at the same time.

Unlike other papers on this topic, we do not pretend to scrutinize sovereign bond spreads determinants, which are different for EMU and non-EMU countries. The aim of this paper is twofold. First, we attempt to reflect the similarities in spreads behavior in a sample of countries. Second, we would like to test if two important structural events (the introduction of a common currency and the financial crisis) affect spreads similarities. For this purpose our sample is composed by EMU and non-EMU countries.

Although SOM methodology has been applied in financial economics, to the best of our knowledge, this is the first empirical study that applies this network architecture to classify and analyze bond spreads.

The structure of the article is the following: section 2 presents a brief review of European bonds spreads evolution. Section 3 introduces self-organizing Kohonen maps. Section 4 presents the methodology and data used to the analysis.

Section 5 shows the empirical results obtained. Finally, section 6 presents the conclusions of the study.

2. European bond spreads: a short review

The preparation for the introduction of a single currency among the European member states began in 1990, entailing the liberalization of capital movements and the beginning of the convergence process. The Treaty on the European Union (commonly known as Maastricht Treaty), is one of the first important rules established for the European Monetary Union (EMU) and the Stability and Growth Pact (SPG). It provided the abolition of national currencies by the common currency and established a set of rules for the economic convergence relative to price stability, exchange rates and public deficit and debt levels for the member countries.

In 1999, the euro was introduced into the world of financial markets as an accounting currency and indicated the effective start of the monetary union. Euro banknotes entered into circulation in January 2002.

Since the inception of the EMU the exchange rate risk between members states disappeared and the financial market became more integrated. Pagano (2004) considers that the EMU opened the possibility for the creation of a new and integrated financial market that through the spillover effect also affected the private bond market.

McKibbin and Bok (2001) highlight some of the benefits of the Monetary Union, considering the reduction in transactions costs associated with the existence of multiple currencies, greater efficiency given the decline of uncertainty related to currency instability and increased credibility of monetary policy within Europe.

Before the introduction of the euro, yield differentials within sovereign European debt instruments were mostly determined by four elements: exchange rate variation, differences in domestic tax-treatments, and liquidity and credit risk (Codogno et al., 2003). The first two factors were eliminated; meanwhile the other two remain relevant.

According to Gómez-Puig (2008), EMU and non-EMU spreads are not commonly affected by the same determinants, being the relative importance of domestic risk factors (credit and liquidity factors) higher than international factors for EMU countries, but the relationship is inverse for non-EMU countries. Abad et al. (2009) analyze the impact of the introduction of the euro over the degree of the integration of European government bond markets applying the CAPM-based model and find that EMU members are less vulnerable to the influence of world risk factors, but more susceptible to the EMU ones. On contrary, Gerlach et al. (2010) consider that the main determinant of spreads, since the introduction of the euro, is the change in the international aggregate risk.

Zunino et al. (2012) find that the stochastic characteristics of sovereign bond time series is different for EMU and non-EMU countries and Bariviera et al. (2012) find that the 2008 financial crisis affected the random behavior of bond returns time series of several European markets.

A liquid market allows investors to make decisions at any time, so the number of financial operations should be considerable to determine the size and depth of the market and the liquidity premium level. Gómez-Puig (2008) affirms that the EMU produced important changes related with the financial integration, especially in the euro area sovereign securities market, even though the market size produces differences between the spreads of diverse members.

Liquidity risk and credit risk are interconnected (Barrios et al., 2009; Arghyrou and Kontonikas, 2011). On the one hand, if a government increases its bonds supply, the pressure on liquidity premium decreases. On the other hand, a high supply is associated with an increase in public debt and deficit, which increases the credit risk premium.

Nonetheless, other studies (Codogno et al., 2003; Geyer et al., 2004) find that liquidity factors play a minor role in explaining EMU government bond yield spreads, being the credit risk a major driving force of systematic risks. Moreover, the international risk is considered an important driver.

Bernoth et al. (2004) find that spreads are affected by international risk factors and reflect both default and liquidity risk premiums. According to Barrios et al. (2009), the combination of high risk aversion and large current account deficits tend to magnify the incidence of deteriorated public finances on government bond yield spreads.

However, the global financial crisis modified investors' perception of risk and the diversification of investment portfolios propagated market risks. European countries are more unstable and the single currency becomes more vulnerable.

The recent financial crisis produced considerable global impact, not only because of its scale but also by the fact that it has been originated in the largest economy of the world. The consequences differ from country to country.

There are two important dates to identify the beginning of the financial crisis. The first one is 15 July 2007, since then the financial companies first began to have negative consequences in the US markets (Bear Stearns, Countrywide, America Home Mortgage). The second one is 15 September 2008, the day on which Lehman Brothers went bankrupt. However, in the literature there is no unanimous consensus about the start date of the split period. Sovereign bond spreads remained relatively stable at a low level and only started to grow in July 2007. According to Aβmann and Boysen-Hogrefe (2009), in mid-2007 the financial crisis took off and had a climax in September 2008 with the collapse of Lehman Brothers. The results of Barrios et al. (2009) are in the same line. Our analysis test the impact of both events on the European spreads.

3. Self-organizing Kohonen maps

Self-organizing maps (SOM) are a particular kind of artificial neural network, developed by Kohonen. According to Kohonen (1989), the artificial neural networks are "massively parallel interconnected networks of simple (usually adaptive) elements and their hierarchical organizations which are intended to interact with the objects of the real world in the same way as biological nervous system do".

This type of artificial neural networks has been applied to numerous studies in the financial context, showing great descriptive and predictive ability (Deboeck and Kohonen, 2000). Although their use is more generalized to analyze bankruptcy prediction and bond rating, in both cases SOM are applied for its clustering capability. This capability is also pursued in this work.

SOM have been applied to problems of grouping in financial markets, as for example to analyze temporary effects in stock markets (Sorrosal and Ramírez, 2009) or to improve the classification of mutual funds (Moreno et al., 2006). Related with financial crises, Sarlin and Marghescu (2011) examine visual predictions of currency crises applying self-organizing maps and conclude that it is a feasible tool which visual capabilities expedite the understanding of the factors and conditions that contribute to the inception of a currency crisis. Similarly, Fioramanti (2008) applies the artificial neural networks, using data since 1980-2004, to predict sovereign debt crisis. Du Jardin and Séverin (2011) apply a self-organizing map to improve a model to predict corporate bankruptcy. They also provide a valuable tool for companies seeking to measure their financial condition through the analysis of the trajectories. In a similar way, Chen et al. (2013) consider a large number of variables, related to the bankruptcy risk of the companies studied and conclude that the self-organizing map is a useful visual data mining approach to explore a large amount of data.

In artificial neural networks there are two kinds of learning process: supervised or unsupervised. In the first case, there is an external agent that compares the output of the network with the desired output and modifies the weights in order to obtain a robust result. In the second case, the network itself fits the output using distance functions that measure the similarity between the input patterns of the system. These kinds of networks with unsupervised learning process have self-organizing capabilities. SOM networks are unsupervised and their main application, among others (e.g. pattern recognition and resolution of optimization problems), is data clustering.

Self-organizing Kohonen maps are formed by two layers of neurons: an input layer with as many neurons (or units) as variables are used to form the patterns, and an output layer consisting of a bi-dimensional map. In other words, the neurons that form the output layer are distributed in rows and columns. The dimension of this layer depends on the amount of data, increasing with the number of patterns.

Regarding SOM architecture, the data introduced into the system are propagated through: (*i*) Feed-forward connections: connections that have their origin in neurons of a layer and destination to neurons from another layer. *(ii)* Lateral connections: connections between neurons in the same layer. *(iii)* Auto-recurrent connections: connections from one neuron to itself.

SOM present the last two connections in neurons of the output layer, allowing in this way the competition process that is suitable for the unsupervised learning of SOM. After the learning process, only one neuron remains active in the output layer. The called 'winner neuron' indicates the place in the map that occupies the pattern whose information has been introduced into the system.

Once the network distributes all patterns in the output layer, they can be grouped. The number of groups is established by an optimization problem with a double objective function, which minimizes the number of groups and at the same time maximizes the homogeneity of the elements within the group. Alternatively, the network designer can determine a specific number of groups.

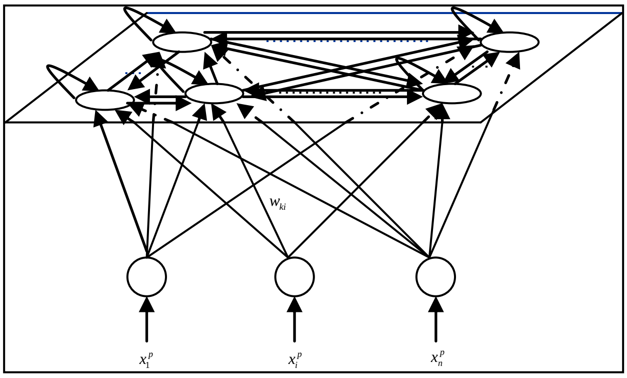

Figure 1. SOM Structure. Own elaboration

Briefly, we can understand how a SOM works through the following steps:

The patterns to cluster are defined using a number n of variables or characteristics according to the purpose of the analysis. In this way, we obtain a set of p patterns like $x^p = (x^p_1, x^p_2, \dots x^p_i, \dots x^p_n)$, where the superscript p indicates the specific pattern and the subscript $i=\{1, 2, \dots n\}$ corresponds to each one of the variables that defines a pattern.

The information is introduced in the network. Each neuron of the input layer takes the value of one component of the vector that represents a pattern. These values are propagated to the output layer through feed-forward connections that join the input neurons to the m neurons that form the output layer. Associated with each connection there is a weight $W_{k,i}$, where the subscript indicates that this weight is related to the connection between the neuron i of the input layer and the neuron $k=\{1, 2, \dots m\}$ of the output layer. Initially, weights $W_{k,i}$ are selected randomly.

For all patterns introduced to the network, the Euclidean distance between a vector and the weights associated to the connections that arrives to each one of the neurons of the output layer is calculated. The distance is measured as using the expression: $d^p_k = [\sum(x^p_{i,} - w_{k,i})^2]^{1/2}$.

From the m neurons of the output layer, the one that presents the least distance among its weights and the pattern introduced into the network is called the winner neuron for this pattern. So, the winner neuron, k^*, is the neuron that satisfies $d^p_{k^*} = \min [d^p_k]_{k=1,\dots m.}$

Once the winner neuron is determined, their weights are modified. This modification and also the changes in the weights of the neurons that belong to the neighborhood area of the winner neuron is the learning process. This neighborhood area is defined during the design of the network and includes, from the winner neuron, all adjacent units according to a rectangular or hexagonal area. This area tends to decrease when the number of iterations increases. This allows the network to converge because the number of neurons that modify their weights decreases with time.

Weights corresponding to period t+1, $W_{k,i}$(t+1), are obtained as the weights at time t, $W_{k,i}$(t), plus an expression that depends on the distance between the component of the pattern and the weight associated with the connection between the neuron of the input layer and the winner neuron, and modified by a coefficient $\alpha(t)$, called the learning coefficient. Thus, the modified weights can be expressed as: $w_{k,i}\ (t+1)= w_{k,i}\ (t)+ \alpha(t)\cdot\ [x^p_{i,} - w_{k*,i}\ (t)]$, where $\alpha(t)$ takes a value between 0 and 1, being a value that decreases with the number of iterations in order to ensure convergence to the equilibrium of the network.

The process continues with the presentation of the rest of patterns and the sufficient number of iterations to get the stability of the association between the different patterns with the same unit of the output layer.

The resulting map provides the distribution of the patterns as a function of the similarity between all their characteristics. To understand the place of a pattern on the map and the behavior of the different groups, it is necessary to know the value of each one of the variables in the map. This information is also obtained from the network through component maps.

4. Methodology and Data

Our database comprises 17 European countries: EMU countries, except Luxemburg[1] (Austria, Belgium, Finland, France, Germany, Greece[2], Ireland, Italy, Netherlands, Portugal and Spain), and non-EMU countries[3] (Czech Republic, Denmark, Hungary, Poland, Sweden and United Kingdom). Germany is our benchmark to estimate bond spreads.

The patterns are defined as vectors of 12 components or variables. The first one is the annual spread of each year of the sample and the rest 11 variables are the spreads variation between two consecutive months, i.e between January and February (variable 2), February and March (variable 3) and so on to November and December (variable 12).

We use the Government Bond Index (GBI) calculated by JPMorgan. The GBI is made up of fixed-rate bonds and domestic bonds of countries that give international institutional investors an opportunity to invest in liquid debt markets. This means that bonds are stable, active and regulary issued.

We select the monthly index that represents government bonds with a maturity between seven and ten years.

[1] Whose public debt is negligible.
[2] Join the Monetary Union later, in January 2001.
[3] European countries incorporated later to the Monetary Union as Slovenia (2008), Cyprus and Malta (2009), Slovakia and Estonia (2011) are not considered given the small size of their financial markets.

Data is obtained from DataStream, for the period 1999 to 2011 measured at the end of each month. There are some exceptions with respect to the period included of three countries, given the unavailability of data. The time series of Poland begins in 2000 and those of Hungary and Czech Republic begin in 2001.

We work with a total of 203 patterns. Each pattern is defined as the standard values of the 12 variables of a country in a given year. Our sample includes data of 10 EMU countries during 13 years, giving a total of 130 patterns; and 6 non euro countries, 3 of them during the same period, and the other 3 contain one and two years less of data, giving a total of 73 patterns.

SOM network is implemented in Matlab using the toolbox developed by the Laboratory of Information and Computer Science in the Helsinki University of Technology.

The input layer of the SOM, in all cases considered, consists of 12 units. Each of them contains the value of one of the variables that define the patterns. Table 1 shows the correlation matrix between the values of these variables for all the analyzed patterns.

Table 1: Matrix correlation

	Var1	*Var2*	*Var3*	*Var4*	*Var5*	*Var6*	*Var7*	*Var8*	*Var9*	*Var10*	*Var11*	*Var12*
Var1	1											
Var2	-0.271	1										
Var3	0.397	-0.086	1									
Var4	0.086	-0.032	0.257	1								
Var5	0.219	-0.112	-0.201	0.193	1							
Var6	0.265	-0.219	-0.097	-0.105	0.214	1						
Var7	0.268	0.051	0.112	0.115	0.619	0.073	1					
Var8	-0.095	-0.221	-0.182	-0.020	-0.042	0.041	-0.132	1				
Var9	0.232	-0.098	0.049	-0.092	0.440	-0.021	0.343	-0.495	1			
Var10	0.426	-0.465	0.265	0.173	0.431	0.226	0.148	-0.060	0.464	1		
Var11	0.361	-0.274	0.289	0.173	0.448	0.174	0.204	-0.106	0.365	0.702	1	
Var12	0.473	-0.412	0.276	0.166	0.567	0.234	0.380	-0.300	0.619	0.808	0.699	1

It can be seen that the largest correlation coefficients correspond to variables 10, 11 and 12. These variables represent monthly spreads variations in the last three months of the year. However, the rest of correlations justify the use of all variables for grouping purposes using self-organizing maps of Kohonen.

The implementation of the SOM network for the whole sample generates as output a map of 9 rows and 8 columns. This is the result of a dual criteria objective function, which minimizes the number of groups and maximizes the homogeneity of the patterns within each group.

When the network is implemented only for EMU patterns, the map is of 9x6 dimension, forming 3 groups. On contrary, when non-EMU countries are considered, the output map is smaller, 7x6, given the lower number of patterns, but it forms 7 groups. This relationship between the number of clusters and patterns evidence a greater homogeneity among EMU countries than among non-EMU countries, with respect to the sovereign bond spreads evolution throughout the year and for different years.

In order to generate more disaggregation among EMU countries, we repeat the analysis for this subsample, forcing the network to establish 7 groups.

The interpretation of the results of the different SOM is described in the following section.

5. Empirical Results

5.1 SOM applied to all countries of the sample

Initially we compute the results considering all countries of the sample. Figure 2 shows the Kohonen map and the grouping related to this first analysis.

Pol00 Spn11 Ita11 Hun11 Port11	Hun03 Irl11	Pol01 Hun02 **1**	Swd99	Ita08 **2**	Chz08 Gre08 Hun08 Pol08	**3**	Gre10 Irl10 Port10 Gre11
Bel11 Pol11	Chz01 Pol06		Swd01 Aus11 Fra11	Aus08 Den08 Irl08 Port08		Hun06	Spn10 Hun10
Gre99 Pol03 Chz11	**4**	Den99 Chz06 UK06 Neth11	Aus99 Ita99 Finl11	Chz07 Finl08 Fra08 Neth08	Bel08 Spn08	Bel10	Hun04 Ita10 Pol10
Irl01 Swd11	Gre01	Gre07 Port07 Ita07	Bel99 Fra99 Spn99	UK01 Irl02 Swd07	Aus10 Swd10 Fra10	**5**	Irl09 Chz10
Swd00 Chz03 Neth10	Aus01 Bel01 Den01 Spn01 Finl01 Fra01 Ita01 Port01	Neth01 Den11	Neth03 Aus07 Bel07 Spn07 Finl07 Fra07 Neth07	Neth00 Finl05 Finl06 Den07 Irl07	Bel00 Spn00 Fra00 Ita00	Aus00 Finl00 Swd02	Port00 UK08 UK09
Bel03 Swd03	Swd05 Den05 Den03	Neth99 Irl05 Neth05 Fra05 Aus05 Neth06 Bel06	Port05 Aus06 Fra06 Spn06 Irl06 Port06 Gre06 Ita06	Neth02	Gre02 Port02 Spn02	Swd08 UK11	Spn09 UK10
Finl99 Aus03 Spn03 Finl03 Fra03 Gre03 Ita03 Port03 UK03	Port99	Neth04	UK99 UK02 Bel05 Gre05 Den06 Swd06	Spn05 Ita05 Finl10 **6**	Irl99 Aus02 Finl02 Bel02 Den02 Fra02 Ita02	Den09 Neth09	Irl03 Bel09 Finl09
Chz05	**7**		Den00		Fra09 Den10	Aus09	Hun07 Pol07 Gre09 Ita09 Port09
Pol04 Hun05 Pol05	Irl00 Swd04	Aus04 Bel04 Chz04 Irl04 Ita04Port04 UK04 Den04 Fra04 Gre04 Spn04 Finl04	Swd09	Gre00 UK00	Chz02 UK05 UK07	**8**	Hun01 Pol02 Chz09 Hun09 Pol09

Figure 2. Kohonen Map. All countries

As could be observed groups 1, 2, 3 and 5 include patterns of countries affected by the recent financial crisis, during the period after the inception of the crisis. Moreover, could be observed that inside these groups there are patterns of years before 2008, which could indicate that those countries have shown earlier high bond spreads variations. In other words, there were countries that acted as early signals of the start of the crisis.

In group 8, there are countries with high yearly spreads, although monthly variation inside this group is moderate (see, e.g. variables 2 to 12 of this group).

On the other side, groups 4 and 6 include two types of patterns: countries that were not severely affected by the crisis or patterns of almost all the countries during the period before 2007. These groups reflect the great homogeneity of a diverse sample of countries since the inception of the euro and during the first years of its consolidation. As could be observed, both groups are predominantly formed by EMU countries, Denmark, Sweden and UK. In Group 7 we detect a predominance of patterns of almost all the countries for year 2004. We will analyze below this situation with more detail.

In order to interpret the behavior of each country-year pattern related with its position in the map, it is necessary to evaluate the value of each variable (normalized) in each area. This information is represented in figure 3, through the scale values represented by colors, which results in numeric scale to the right of each map. In all cases, the dark blue color indicates the minimum values of each variable, while red indicates the highest values.

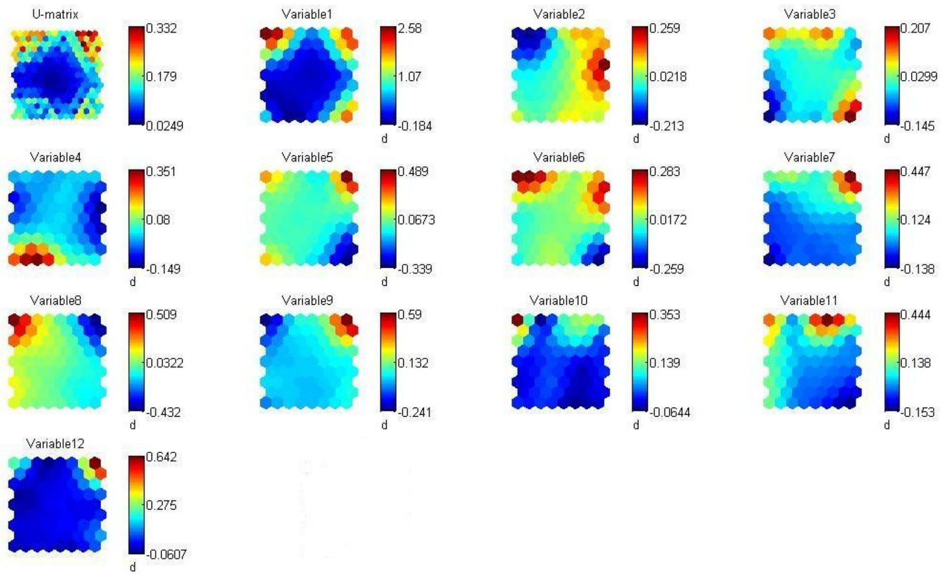

Figure 3. Distance and Components Maps. All countries

Considering the distribution presented in variable 1 (annual sovereign bonds spreads) in the characteristics map, we see that in the center of the map are located patterns with the lowest levels of annual spread, while the extremes are countries with the highest levels.

This distribution is related with the financial monetary integration. As could be observed in the central zone of the map, groups 4 and 6 concentrate country-year patterns of EMU members during the period of the euro zone consolidation.

This distribution is not casual. Since 1999 some EMU members presented similar bond spreads variations such as Belgium, Spain, France and similarly Austria and Italy. The rest of countries presented independent variations to the rest of the set of countries.

According to our results, there is an increase in the homogeneity among EMU members since year 2000. The associations become stronger between 2003 until 2007. During this period the euro zone seems a compact area, with similar spreads levels and evolution. In coordination with EMU countries and during the same time period, Denmark, Sweden and, to a lesser extent, the UK move in harmony with the euro zone. It is important to highlight some features of these countries, such as their large sizes, solid economies and sustained coordination with the main European countries.

However, the rest of non-EMU countries of the sample (Czech Republic, Poland and Hungary) present an independent and scattered behavior of each country-year pattern. Their map localization represents high spread levels.

One of the reasons of this behavior is that they are countries with economies in transition. Their late inclusion as members of the European Union in 2004 also justifies the lack of coordination from the rest of the countries analyzed.

As has been mentioned, group 7 is constituted predominantly by patterns related to the year 2004 of all countries of the sample, except Hungary and Netherlands. The main feature that distinguishes this group is the high value that takes the variable 4 (the spread increased from March to April) respect to the rest of the groups. This behavior is not unusual for the year 2004, since the first of May of that year, Czech Republic, Poland and Hungary joined to the European Union. Therefore, a possible explanation for the significant variations in spreads could be by the fall in the rate of the German benchmark bond, consolidating even more firmly in the market as a benchmark.

Continuing the chronological analysis of the results, we can observe that since 2008 there is an increasing dispersion among EMU members as a result of the contagion effect of the financial crisis.

As mentioned, the recent crisis had its beginning in July 2007 in US, but the contagion effect and the significant impact over financial markets deepened since 2008, after Lehman Brothers fall.

In general all countries were influenced by the effect of the financial crisis. This effect could be observed by a movement of countries since 2008 from the central zone of the map to outer areas, where the patterns show higher spreads values. The higher spreads variations in 2008 were for Chez Republic, Greece, Hungary, Italy and Poland.

Subsequently, in 2009 the largest increases in sovereign bond spreads are presented for the following EMU members: Greece, Ireland, Italy and Portugal. As well as for the three smaller economies compared to the rest of European countries analyzed: Chez Republic, Hungary and Poland.

In 2010 sovereign bond spreads variations are still growing in the countries just mentioned. Spain joins this group and presents a critical position for 2011. In turn, Belgium during this last year also presents significant variations in relation to the spread levels. It is a new member of the peripheral euro group. The main reason that locates this country inside this group is the political crisis related with the absence of government for over a year coupled with the poor performance of its growth.

Related to the monthly spread variation throughout the year (see figure 3) a heterogeneous behavior could be observed. However, the maximum variation values remain in all cases at the upper ends (this location coincides with patterns that have higher annual spreads). The variable 4 is an exception, as has been previously mentioned.

Another aspect to highlight is the small variation that shows the monthly spreads in the last quarter of the year. Particularly, respect to October, (variable 10) and December (variable 12), whose the highest values are limited to spread increases supported by countries with greater difficulties during 2010 and 2011.

At the other extreme is the variable 2 (spread variation of February) that takes the minimum values in the area corresponding to countries with higher debt spreads in 2011.

5.2 SOM applied to EMU countries

In order to study in more detail the Eurozone evolution behind the introduction of the euro and the impact of the financial crisis, we have analyzed sovereign bond spreads variations considering only EMU members in the neuronal analysis.

It is relevant to highlight that in the first attempt the neural network gives the variables grouped into three groups. A great one which includes more than a half of the countries and years analyzed, and others two which consider the last critical years for some countries. With the purpose of performing further analysis within this large group that reflects the period of stability in the euro-zone, we have implemented the SOM again but establishing a priori the number of groups that the network should be established, setting this number in 7 groups. Figure 4 shows the grouping. For the results interpretation, use figure 5.

In the same line of analysis of the previous section, we perform a chronological study since 1999. As could be observed, patterns for 1999 and 2000 are located mainly in group 1, although there is some dispersion within the group (there is no an apparent grouping of countries in 1999 and 2000 in the same cell).

The results obtained coincide with the ones from in the general analysis which includes all the countries of the sample. The period since 2001 to 2007 is considered as years of stability and homogeneous behavior in terms of spreads evolution for all countries of the EMU. Particularly, in 2001 all patterns are located near areas of the map. Subsequently, the years 2002 and 2003 have similar characteristics as grouping. In the same cell are included 8 out of 10 members of the EMU countries studied.

Finl99 Gre99 Aus03 Bel03 Finl03 Spn03 Fra03 Gre03 Ita03 Port03	Bel01 Spn01 Fra01 Irl01 Ita01	Irl99 Aus01 Finl01 Port01 Finl10	Gre00 Aus02 Bel02 Spn02 Finl02 Fra02 Gre02 Ita02 Port02	Spn09 Neth09	Irl03 Bel09 Gre09
	Gre01	Aus10		Finl09	Aus09 Irl09 Ita09 Port09
Aus99 Fra99 Neth10	Neth03 Aus05 Ita07 **1**	Neth01 Fra05 Neth06	Neth02 Finl05 Irl05 Aus06 Bel06 Spn06 Finl06 Fra06 Port06	Neth00	Fra09 **2**
Spn07 Gre07 Port07	Neth99 Neth05 Aus07 Finl07 Bel07 Fra07 Irl07 Neth07	Bel05 Spn05 Gre05 Port05 Gre06 Irl06 Ita06	Finl08	Spn00 Bel08 Spn08 Aus11	Port00 Ita08 Port08
Bel99 Spn99 Ita99 Irl02 Finl11 Neth11			Ita05 Fra08	Fra00 Ita00 Aus08 Neth08	
Port99 Neth04				Aus00 Bel00 Finl00	Bel10 Fra10
		Irl00 Aus04 Bel04 Spn04 Finl04 Fra04 Gre04 Ita04 Port04	**3**	**4**	Ita10
					Spn10 Gre10 Port10
Spn11 Irl11 Ita11 Port11	Bel11 **5**	Fra11 **6**	Irl08 Gre08	**7**	Irl10 Gre11

Figure 4. Kohonen Map. EMU countries

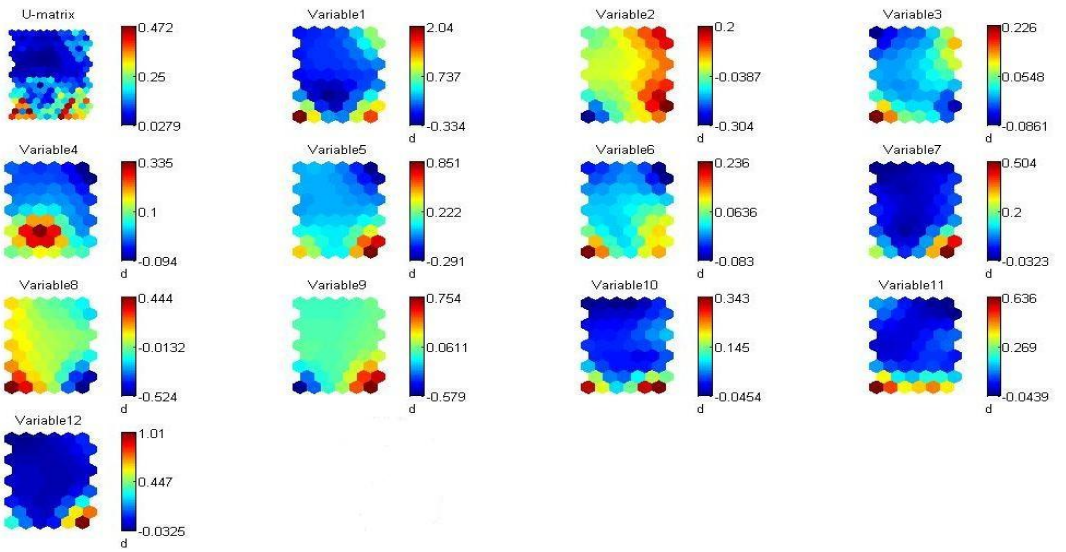

Figure 5. Distance and Components Maps. EMU countries

Ireland and Netherlands have a slightly different behavior. The year 2004 is the one with greater homogeneity, as 9 out of 10 countries considered are in the same representative neuron in the Kohonen map, being the only nonblank cell in the group 3. Moreover, the high values of the variable 4, which represent changes in spreads form March to April, is the main feature of this group. Netherlands diverges once more from the rest of the great group during this year and it states in the group 2.

From 2005 to 2007 there are interesting country groupings which show the existence of important similarities in background levels of spreads variations. All patterns of the sample during this time period are in group 1. That is, not only the yearly spreads level is similar for all the euro zone countries, besides its evolution has evolved intra evenly.

During the years previous to the start of the financial crisis, there are not high variations in the spreads levels in any of the cases analyzed. (See figure 4)

Since 2008, the financial crisis impact over public debt markets of European countries is observed by the great dispersion of variables and its location according to figure 4 in cells that represent higher levels of variation. However, its location is still close, except for Greece and Ireland, which suffer the crisis impact at once and during that year are placed in the group 6.

In 2009 all countries of the sample were affected by greater spread variations, especially at the beginning of the year, when variable 2 (spread variation from January to February) gets high values. This situation depends on each particular case, being as a result of a down grade of the benchmark and not a necessary increased in the price of risk of each market. In 2010, there is a certain grouping among the countries most affected by the impact of the financial crisis: Spain, Greece, Ireland and Portugal in the group 7. Furthermore, Austria, Netherlands and Finland had a good behavior of their sovereign bond spreads, and for that reason they stay in the group 1.

In 2011, Ireland, Italy, Portugal and Spain are in the same unit of the group 5. This location, according to the variable 1 of figure 5, represents the highest value reached during the yearly spreads of all period of analysis. Within this same group, but in a smaller scale variation, we note the presence of Belgium. In group 7 are placed Greece and Ireland with data from 2010.

Therefore, according to the observed distribution of countries of the euro zone, we conclude that the evolution of changes in spreads is predominantly annual and gathers those similar economies related with the sovereign bond spreads variations. While before the start of the crisis was a tendency to homogeneity, the financial crisis highlights the hidden differences between euro zone members.

5.3 SOM applied to Non-EMU countries

We continue the analysis considering only the non-EMU members of the sample to apply the SOM. Figure 6 represents the two-dimensional map (the output layer of the SOM) and Figure 7 shows the Kohonen feature maps for the interpretation of the location of the patterns on the map.

Chz09 Hun09	Pol04	Den04 Swd04 UK04 Chz05 Swd09		Hun05 Pol05	Pol00 Pol03
Chz02	UK00 UK07		Den00 Den08	Chz10	UK08 UK09 Chz11
Hun01	Chz04 UK05 Den11 **1**	Den02 UK03 **2**	UK01 UK02 Den05 Den06 Swd06 Den07 Swd07	UK99 Swd00 Den01	Swd01 Chz03 **3**
	Swd02 Swd10	Den03 Swd03 Chz07 Den10	Chz06	Den99 Swd11	
Chz08 Hun08 Pol08	Den09 **4**	Swd08 UK10	Swd99 Swd05 UK06		Chz01 Pol02 Pol11
	UK11	**6**	Pol06	**7**	Hun03
Hun06 Pol09 **5**	Pol01 Hun04		Hun07 Pol07	Hun10 Pol10	Hun02 Hun11

Figure 6. Kohonen Map. No- EMU countries

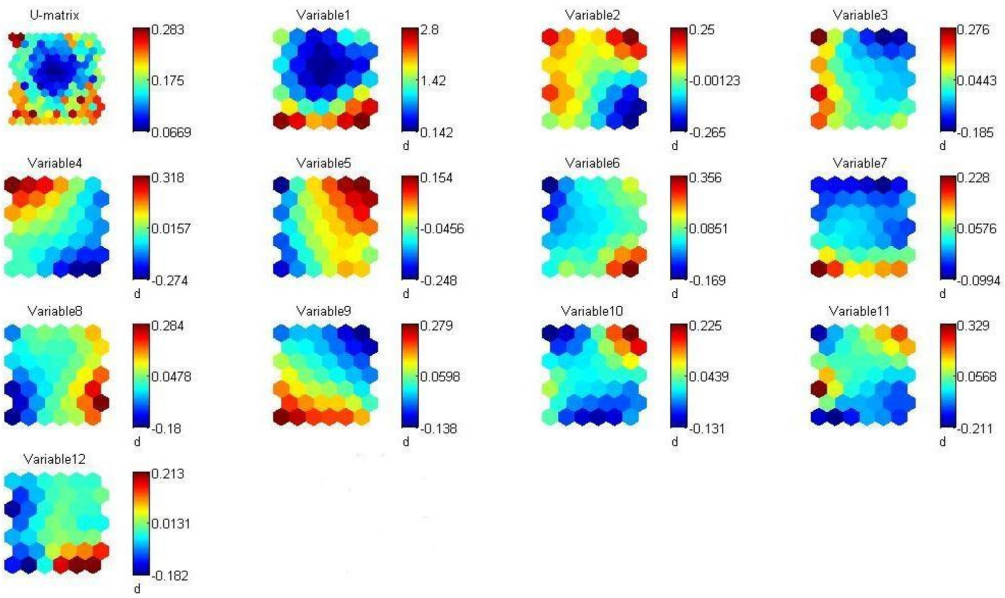

Figure 7. Distance and Components Maps. Non-EMU countries

Without any initial setting of the number of groups to form, considering the criterion of minimizing the number of groups and maximizing homogeneity, the network established 7 different groups. If we compare this number with the original one (3) of the groups obtained for EMU countries (being this sample bigger) gives the sign that the behavior of countries outside the EMU in terms of spreads evolution is much heterogeneous than in EMU countries.

Furthermore, the heterogeneity of the sample countries is also seen in the composition of different groups. There is no a solid classification by countries as in the previous analysis. Anyway, tend to exist certain country grouping. Thus, on the one hand are located the strongest economies (Sweden, Denmark and UK) and on the other side are Czech Republic, Hungary and Poland. However this classification is not solid in all the years of the analysis.

The consolidation of the group 2 is relevant to highlight, since nearly all its components are Denmark, Sweden and UK. This group is the one with greater stability, i.e, variable 1 takes low values and thus indicates a moderate level of annual spreads and the rest of the monthly variables also present small values over the group 1.

Moreover, groups 5, 6 and 7, located in the lower area of the map, are formed primarily by patterns related to Hungary and Poland in different years. Their location, according to variable 1, shows that the combination country-year has suffered higher levels of annual spreads. The specific position in one of the three groups is explained by an uneven performance in the evolution on different months.

Related to Czech Republic is the country which presents evolution, since there are wide variations across the years and their inclusion in different groups.

Regarding to the impact of the crisis over these economies, we can observe that in some way all of them were hit by the financial crisis; although the three weakest such as Czech Republic, Poland and Hungary did so at higher levels. In turn, UK also showed significant variations in the level of spreads. Sweden seems to have been the least affected.

6. Conclusions

In this paper we analyze bond spreads evolution of the several Euroepean countries from 1999 to 2011. We focus on their behavior during two events that take place during this period: the introduction of the common currency and the present financial crisis. We apply a thought-provoking methodology, self-organizing Kohonen maps, because of its capability to cluster elements according to the overall similarity. Moreover, this type of artificial neural network is a network with unsupervised learning that makes unnecessary to define *a priori* groups.

When we consider all countries together, we obtain that during 1999 and 2000 there is not a clear cohesion in the spread evolution of the different countries. However, we find a similar trend from 2001 (especially in UME countries and Denmark, Sweden and UK) and, coinciding with the start of the euro circulation in 2002, this homogenous evolution remains until 2007. This is a stable period with moderate levels of spreads. The year 2004 presents a remarkable increase in the April spreads, pointing out uncertainty about the forthcoming incorporation of Czech Republic, Poland and Hungary to EU. From 2008, start of the financial crisis, it appears again some dispersion between the spreads evolution of the countries. This divergence is greater between EMU and non-EMU countries, and in EMU countries we observe a significant increase in the level of spreads of Greece, Ireland, Italy and Portugal in 2009, jointly with Spain and Belgium afterwards.

Analyzing only EMU countries, we find a high degree of homogeneity between the bonds spreads evolution. The groups that we obtain from the self-organizing map clearly show a joint evolution until the beginning of the crisis. Thereafter, their behavior leads to other groups that are distinguished by higher levels of spreads that increase over time, focusing on countries with large debt problems mentioned above.

In contrast, in the non-EMU countries analysis, we obtain more heterogeneity. It is not possible to find a chronological association by years. That is to say, groups are not formed by years but by countries. Thus, the spreads evolution of Sweden, Denmark and UK is shown relatively aligned. But the arrangement between the Czech Republic, Hungary and Poland is smaller, especially for the Czech Republic.

This study could be of interest for policy makers in order to analyze the consequences of crisis transmissions in sovereign bond markets.

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