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USING SELF-ORGANIZING MAPS FOR ASSESSING SYSTEMIC RISK. EVIDENCES FROM THE GLOBAL ECONOMIC CRISIS

Abstract. *The importance of correctly assessing systemic risk has increased substantially after the events from 2007. A wide set of parametric and non-parametric methods has been used to address the problem and identify the leading risk factors for potential crisis situations. Out of these, the class of neural networks represented by self-organizing maps has become an important technique but only with a modest usage for the economic crisis. We apply the self-organizing maps technique for a set of worlds' economies, with the goal of identifying the resemblances and differences between worlds' economies. The model developed on self-organizing maps ensures detection of the imbalances and vulnerabilities of economies and find the determinant variables (early warning signals) for a financial-economic crisis situation. The study has the advantage of including in the analysis a pre-crisis and a post-crisis assessment, gaining much insight from the structural changes produced in the topology of the economies.*
Keywords: *Self-Organizing Maps, Neural Networks, Early Warning Systems, Systemic Risk, Global economic crisis.*

JEL Classification: C45, H63, C49

1. Introduction

The globalized financial environment that we are experiencing nowadays creates the premises for the financial instability to be transmitted over the countries which could lead to a generalized collapse of the real economy. Apparently, although the stress tests performed on European level gave good results, the credit ratings for many countries in Europe worsened during 2011. Miricescu (2014) makes an analysis of the dominant factors that impact the long-term sovereign rating. In his paper, he highlights the government debt to GDP ratio which raised for the EU from app. 62% in 2000 to 88% in 2014. In this context, the problem of finding and evaluating an accurate early warning system for the European financial system becomes a real challenge and of utmost importance. Many papers have investigated what were the causes of the crisis. For example, Reinhart and Rogoff (2008) find the following lead indicators of crisis: real housing and equity prices, current account deficits, GDP growth, increases in debt.

Recent financial crisis has demonstrate that the economies are vulnerable in front of the systemic financial distress and that it very important for policy makers to understand the sources of these vulnerabilities in order to increase the capacity for absorbing shocks of the financial and economic system. Moreover, the financial integration which is a very wide phenomena (Moscalu, 2014) leads to significant linkages across markets, so that a holistic approach of the financial crisis has to be applied.

Especially after the eruption of the global crisis in 2007, the importance of understanding and correctly assessing risk factors and risk transmissions within markets of the economy has risen as a particularity of assessing financial instability situations. As a general definition (Oet et al, 2010), the early warning systems are "data-driven approaches" with the goal of identifying variables associated with past crises and alert policy makers of other potential future crises. Early warning systems are based on the assumption that crisis factors can be identified before a crisis and can be used for improving policy measures at macroeconomic level.

Objective of the paper is twofold: identification of resemblances and differences between different economies of the world in order to detect the imbalances and adjust the corrective policy as to take into account this disequilibrium; find the determinant variables (early warning signals) for a financial-economic crisis situation.

Structure of the paper is as follows. In section 2 we review the specialty literature of using Self-Organizing maps in the context of the global financial crisis. In section 3 we introduce the basics of the self-organizing maps (including vector quantization concept) and in the next section we present briefly the algorithm of the method. The second part of the paper is dedicated to the case study – we introduce the database, the variables, the topology of the economies before the crisis (2007) and the structural mutations that took place in the post-crisis context. Last section draws the conclusions.

2. Using Self-Organizing Maps for assessing the global financial crisis – Literature review

The main advantage of the neural networks is the fact that they are non-parametric models that do not require the assumptions for statistical data distribution and are not limited by linear specifications. Considering that the indicators of a financial crisis are non-linearly related (Fioramonti, 2008), neural networks were widely used for evaluating the financial, debt or currency crisis. However, the focus of the current paper is on the self-organizing maps, as a class of the neural networks models, so we will provide the literature review of using this technique in assessing financial stress. Despite the large number of papers that study the use of SOM in engineering or medicine, the specialty literature is whatsoever scarce in what concerns the applications of SOM in financial stability and economic crisis assessment.

First studies that apply SOM to model currency crisis are that of Arciniegas and Arciniegas Rueda (2009). They explore the correlation between real effects of speculative attacks on currency and a set of macroeconomic variables. In Sarlin and Marghescu (2011) we have the same idea, of applying the SOM for the indicators of a currency crisis. Dattels et al. (2010) develop a Global Financial Stability Map, by using six composite indices. However, it has the disadvantage that the sources of individual stress are difficult to identify and, as stated by the authors, the results are to be viewed as illustrative.

Sarlin, Peltonen (2011) develop a Self-Organizing Financial Stability Map (SOFSM) which allows the identification of the vulnerability sources and performs well for out-of-sample systemic financial crisis. For the topologically ordered SOFSM, the financial stability neighborhood represents the "contagion of instabilities through similarities in the current macro-financial conditions". The map is represented in the following areas of the financial stability cycle: pre-crisis, crisis, post-crisis and tranquil state. The SOFSM developed performs better than a logit model for classifying in sample data and for predicting the global crisis from 2007. However, the map does not show the imbalances between different economies across the world facing the economic crises.

Itturiaga and Sanz (2013) propose a model for detecting and managing divergences between countries in order to anticipate the danger of a financial crisis. They use the Self-Organizing Maps model to perform a classification of the European countries, as well as German and Spanish regions. The reason for choosing these two countries comes from the similar territorial organization but with the significantly different financial status. The SOM model is applied to find the extent to which national financial instability is due to the regional macroeconomic imbalances. Public expenditure and saving rate are found to be the most critical variables with impact on a country's economy.

A worth to mention adaption of the Kohonen standard SOM is the Self-Organizing Time Map designed by Sarlin (2013a, 2013b) with the purpose of abstraction the structure in temporal multivariate problems. When ordering ascending of time the one-dimensional arrays, the SOTM will enable a two-dimensional representation with the multivariate data structures on the vertical and the temporal direction on the horizontal. The ordered SOTM can be used for projecting individual or grouped data onto the map. In Sarlin (2013b), the SOTM is applied to financial stability surveillance. The results show that high equity prices, current account deficits and GDP growth are the main triggers for financial crises. The Self-Organizing Time Maps can be used for: identifying the imbalances in indicators over time, the structural changes in data, the specific location of univariate and multivariate changes across the data.

As also it was mentioned in Sarlin, Peltonen (2011), the SOM applied for assessing financial and economic crisis "enables disentangling the specific threats, risks and triggers, and should be treated as a starting point rather than an ending point for financial stability analysis”.

3. Self-Organizing Maps – Essentials

Neural networks can be classified in two major classes: supervised and unsupervised networks. For the supervised ones, a target vector is presented to the network so that it adjusts the results to the expected output. The unsupervised networks are assimilated to the exploratory analysis and clustering methods. The Self-Organizing Map is an unsupervised competitive type of network.

The first scientists to delimitate the notions of brain maps are Mountcastle (1957) and Hubel and Wiesel (1962). They found that certain neural cells in the brain react to specific sensorial stimulations. Moreover, the designated cells are grouped in local assemblies and their location is assigned with the response to a certain stimulus. This is the way the brain maps, which are nothing less than systems of cells, have been discovered and defined.

Later on, Merzenich et al. (1983) has reported that the brain maps depend strongly on sensorial experiences. This idea has developed into the competitively learning neural networks. This means that in a sequel of cells, the process of cells' adaptation to the input signal makes them dependent on the specific input characteristics.

However, the brain maps models which were inspired by biology could not be applied to data analysis, and this was mainly due to the fact that the resulting maps were partitioned, meaning that they were made of several patches, between which the ordering was random and discontinue, so no global order existed over the entire map.

That is why, in the neural models used in data analysis, controlling the nodes activities through the neural connections is not enough. There is a need for an extra control, using factors to intermediate the information without mediating the activities. This is where the vector quantization comes into place.

The idea of vector quantization (VQ) dates back to 1850 (Dirichlet) and 1907 (Voronoi tessellation in spaces of arbitrary dimensionality). This technology used in digital signal processing, partitions the vector-values input data into a finite number of contiguous regions, where each region is represented by the single model vector or the codebook vector. The VQ is usually illustrated with the Euclidean distance. For instance, if we consider the input data formed of n-dimensional Euclidean vectors, denoted by Y and the model vectors denoted by M_i . We denote with M_w the winner model vector, the vector with the smallest Euclidean distance from the input vector, Y. Mathematically, we can write:

$$w = arg \min_i \{\|Y - M_i\|\} \qquad (1)$$

If we further denote with f(Y) the probability density of Y, the mean quantization error E is then defined as:

$$E = \int_V \|Y - M_w\|^2 f(Y) dV \qquad (2)$$

Where dV is a volume differential on the data space V. The objective function, E, is an energy function which could be minimized by the gradient descent procedure. (Kohonen, 2013).
The above outlined VQ technique is also called the "k-means clustering" and the self-organizing map can be viewed as a generalization of the k-means clustering algorithm. The self-organizing map is first introduced by Kohonen at the beginning of the 80s. The technique resembles the VQ, but the vector models are spatially and globally ordered. In Figure 1, we represent a self-organizing map – for an input vector Y, the feature map finds the winning node in the finite output space. The associated weight vector give the coordinates of the node from the input space.
As per Kohonen (2013), the input data, Y, is mapped to a set of models (M_i) where $M_w$is the best match for Y. All models that are in the close surrounding of the winner model are better match with Y than the others. The figure illustrates the basis of the Self-Organizing Maps (SOM) algorithms. Similar models will be assigned with nodes that are closer in the grid (smaller Euclidean distance in the VQ), while less similar models will localized further away. The essentials of the SOM, as stated by Kohonen (2013) is: "Every input data item shall select the model that matches best with the input item, and this model, as well as a subset of its spatial neighbors in the grid, shall be modified for better matching". The mentioned modification is associated with the winner model. However, due to the fact thatit is not a single vector that changes, but an entire family of neighbors vectors, this implies a local ordering of the models in the neighborhood. This local ordering will propagate across the grid.

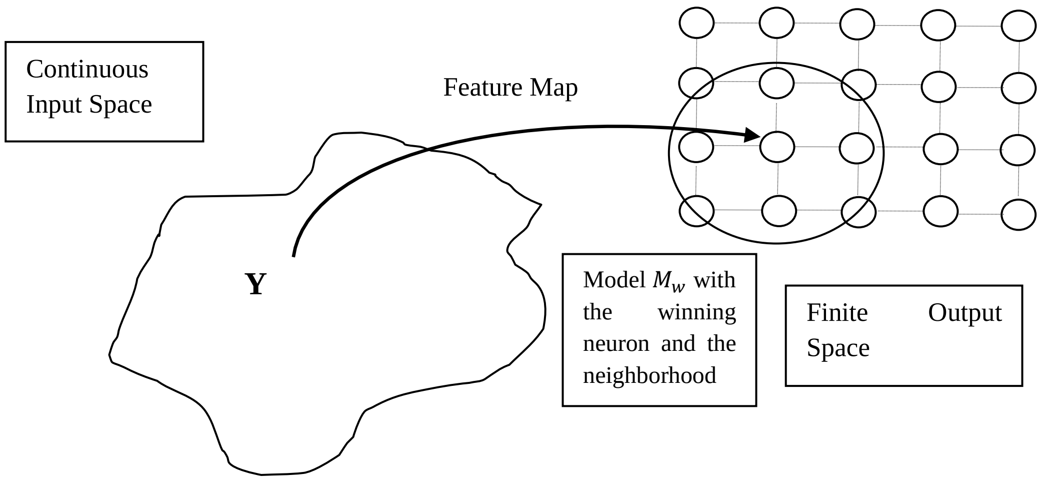


Figure 1 – Feature Map – Self Organizing Map representation

Two algorithms can be used for producing an ordered set of models in the map. The first one assumes a stepwise procedure, meaning that the input data are presented to the network one at a time, for as many iterations as necessary to reach a state of equilibrium. In the second type of algorithm, all input data are presented to the algorithm as one batch and all the models are modified in a single operation. The batch process repeats a certain number of times until the exact stabilization of the models. In the second type of algorithm, the state of equilibrium is attained faster than in the first one.

4. The Algorithm used for training the Self-Organizing Map

The basic Kohonen network has a layer of input nodes and only one layer of output neurons. The neurons from the first layer form a discrete topological mapping of an input space, $Y \epsilon \mathrm{R}^n$. The algorithm is based on minimizing the distances between the nodes, and as mentioned before on the Vector Quantization idea.

The initial step (step zero) of the training algorithm consists in initializing all weights of the network $\{w_1, w_2, \ldots, w_M\}$with small random values. We mention that: w_i is a weight vector associated with the neuron "i", having the same dimension, n, as the input vectors; M is the total number of neurons in the input space and suppose that l_i is the location of vector "i"on the grid.

For the first phase of the algorithm, in the first step an input training vector, Y(t) is chosen from the input space and presented to the grid. The second step of the algorithm consists in examining every node of the network and finding the winning neuron, that is, the neuron having the weight vector closest to the input vector, in terms of distances (for example, in eq. 3 the Euclidean distance is used):

$$\min d_j(y) = \sqrt{\sum_{i=1}^{n} \left(y_i - w_{ji}\right)^2} \tag{3}$$

$$v(t) = \arg\min_{k \in \Omega} \|Y(t) - w_k(t)\| \tag{4}$$

whereΩ is a set of neuron indexes.

In the second phase of the algorithm, the weights of the winning neuron and its neighbors are updated as stated in equations 5 and 6.

$$w_k(t+1) = w_k(t) + L(t) n(v, k, t)[Y(t) - w_v(t)] \tag{5}$$

or otherwise stated:

$$\Delta w_k(t) = L(t) n(v, k, t)[Y(t) - w_v(t)] \tag{6}$$

Where:

$L(t)$is the learning rate of the network. These coefficients are scalar-valued that decrease monotonically and satisfy the following properties (7):

$$0 < L(t) < 1; \quad \lim_{t\to\infty} \sum L(t) \to \infty; \qquad \lim_{t\to\infty} \sum L^2(t) < \infty \qquad (7)$$

$n(v,k,t)$ is the neighborhood function, which in practice has the form of a Gaussian function, as in (8):

$$n(v,k,t) = \exp\left[-\frac{\|l_v - l_k\|^2}{2\sigma(t)^2}\right] \qquad (8)$$

Where l_i is the location vector of neuron "i" and σ represents the range or the radius of the neighborhood, which decrease monotonically with time. The Gaussian function is introduced in the adjusting equation inorder to give lower importance to the neurons of the neighborhood that are situated further away from the main node found as the BMU (Best Matching Unit) of the input neuron.

The algorithm is than reiterated from the first step (choosing the input neuron) until the map converges. The algorithm was presented as stated by Kohonen (2013) and Yin (2008).

After the convergence of the SOM algorithm, the feature map has important statistical properties (these are also mentioned in some Lecture Notes from J.Bullinaria, 2004). First of all, the feature map which consists basically of a set of weights in the output space offers a good approximation of the input space. This is exactly the basis of the Vector Quantization theory that we explained in the previous section and which is the foundation of the dimensionality reduction process.

Secondly, the feature map is topologically ordered, meaning that the space of a neuron in the output layer corresponds to a certain partition (feature) of the input neurons. This is an immediate consequence of the weight update equation (eq. 4), which is applied to all the nodes of the neighborhood and not only to the winning neuron. That is why, the map is considered an "elastic" net – as the neuron in one neighborhood are connected through the correspondents in the input space, than the network will offer an image that is linked to the topological ordering of each stage of the network training.

The third property of the feature map refers to the variation in the input distribution. The regions where training vectors are drawn with high probability of occurrence will be mapped into wider partitions of the output layer and with a better resolution. Property three of the feature map will be illustrated in the case study with the outliers distribution on the network.

The fourth property of the feature map states that the Self-Organizing Maps are able to select the best features irrespective of the distribution in the input space, that is they perform very well even for non-linear data. This is a very important highlight, especially compared to other dimensionality reduction techniques, like Principal Component Analysis which can be applied only if the data is linear.

Otherwise said, the SOM can be viewed as an non-linear generalization of the Principal Component Analysis, as it offers a solution for finding principal surfaces or curves.

5. Case study

In the case study, we propose applying the Self-Organizing Map model to a set of world economies, for two key periods: 2007 – the year before the eruption of the crisis and 2010, the aftermath of the crisis. The inputs of the network are a set of macroeconomic variables registered in the two periods. The results of the map are numerous. First of all we obtain the topology of the economies before the eruption of the crisis and the structural changes that appeared after the crisis,that is how the world map changed from an economic point of view. Secondly, we analyze the distribution of the macroeconomic variables across the countries for the two periods and find the early warning signals of a crisis.

5.1 Data Base

The Data Base constructed is formed of 15 variables, which are detailed in Table 1. Data sources include: World Bank, CIA World Fact Book, Eurostat. Decision upon variables included in analysis follows the specialty literature, like Sarlin and Peltonen (2011), Iturriaga and Sanz (2013).

Table 1 – Macroeconomic variables included in analysis (source of metadata: World Bank)

V1	Agriculture, value added (% of GDP) Agriculture corresponds to ISIC divisions 1-5 and includes forestry, hunting, and fishing, as well as cultivation of crops and livestock production.
V2	Cash surplus/deficit (% of GDP) Cash surplus or deficit is revenue (including grants) minus expense, minus net acquisition of nonfinancial assets. This cash surplus or deficit is closest to the earlier overall budget balance.
V3	Domestic credit provided by financial sector (% of GDP) Domestic credit provided by the financial sector includes all credit to various sectors on a gross basis, with the exception of credit to the central government, which is net.
V4	GDP per capita (current US$) GDP per capita is gross domestic product divided by midyear population.
V5	GDP growth (annual %) Annual percentage growth rate of GDP at market prices based on

	constant local currency.
V6	Central government debt, total (% of GDP) Debt is the entire stock of direct government fixed-term contractual obligations to others outstanding on a particular date.
V7	Gross savings (% of GDP) Gross savings are calculated as gross national income less total consumption, plus net transfers.
V8	Industry, value added (% of GDP) Industry comprises value added in mining, manufacturing (also reported as a separate subgroup), construction, electricity, water, and gas. Value added is the net output of a sector after adding up all outputs and subtracting intermediate inputs.
V9	Inflation, consumer prices (annual %) Inflation as measured by the consumer price index reflects the annual percentage change in the cost to the average consumer of acquiring a basket of goods and services.
V10	Interest rate spread (lending rate minus deposit rate, %) Interest rate spread is the interest rate charged by banks on loans to private sector customers minus the interest rate paid by commercial or similar banks for demand, time, or savings deposits.
V11	Money and quasi money growth (annual %) Average annual growth rate in money and quasi money. Money and quasi money is frequently called M2.
V12	Market capitalization of listed companies (% of GDP) Market capitalization (also known as market value) is the share price times the number of shares outstanding.
V13	Bank nonperforming loans to total gross loans (%) Bank nonperforming loans to total gross loans are the value of nonperforming loans divided by the total value of the loan portfolio (including nonperforming loans before the deduction of specific loan-loss provisions).
V14	Stocks traded, total value (% of GDP) Stocks traded refers to the total value of shares traded during the period. This indicator complements the market capitalization ratio by showing whether market size is matched by trading.
V15	Unemployment, total (% of total labor force) (modeled ILO estimate) Unemployment refers to the share of the labor force that is without work but available for and seeking employment.

The variables from Table 1 are recorded for a sample of 80 countries[1], chosen based on the percentage in global GDP and availability of the data .Although we identified a set of outliers in the data, we decided to keep the respective economies in the analysis considering the importance of the respective economies for the study. We mention that Macedonia, Bosnia and Herzegovina and Armenia are outliers (upper limit) for unemployment, with the highest values from the series. The economy of Qatar records an extremely high value for the Value added in industry, while Norway is situated at the upper limit of the Credit surplus and Canada at the lower limit of Money growth. On the other hand, Nigeria is situated at the other extreme, with a very high value for the Money growth and Ukraine at the upper limit of the rate for Non-performing loans. We will observe that these outliers will be counted as such also in the construction of the map.

5.2 State of the economies in 2007 determined by the SOM model

Due to lack of data for the entire sample, the variables Government Debt (V6) and the Interest rate spread (V10) were removed from the list of inputs. We use the variables registered at 2007 and after applying the algorithm, we obtain the map in Figure 2. The80 countries from the sample are grouped on 9 regions, three dominant ones comprising 62 countries out of the total.

We will start by analyzing the first group of countries (center, blue in Figure 3) which is also the most numerous. The 26 countries can be classified geographically as follows:

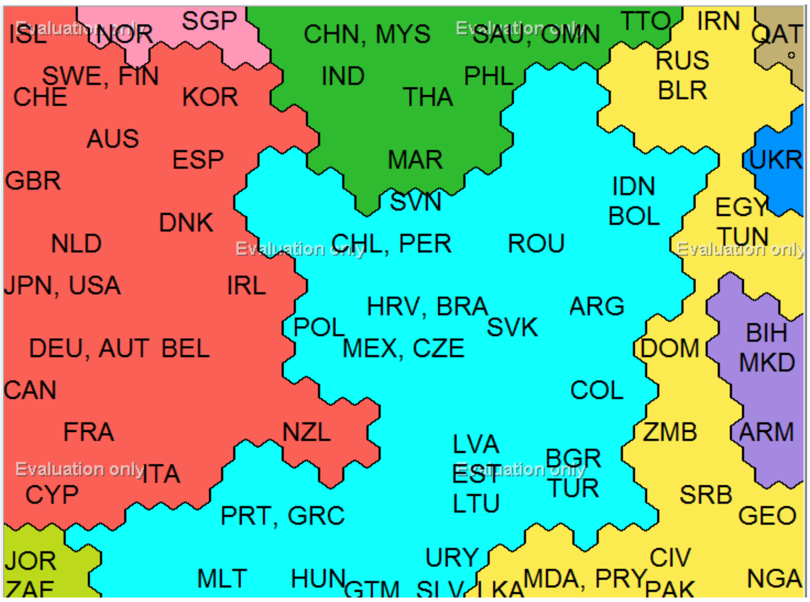
- Latin America: Chile, Bolivia, Peru, Argentina, Mexico, Colombia, Uruguay, Guatemala, El Salvador, Brazil.

[1]Argentina, Armenia, Australia, Austria, Belarus, Belgium, Bolivia, Bosnia and Herzegovina, Brazil, Bulgaria, Canada, Chile, China, Colombia, Cote d'Ivoire, Croatia, Cyprus, Czech Republic, Denmark, Dominican Republic, Egypt, El Salvador, Estonia, Finland, France, Georgia, Germany, Greece, Guatemala, Hungary, Iceland, India, Indonesia, Iran, Ireland, Italy, Japan, Jordan, Korea Rep., Latvia, Lithuania, Macedonia FYR, Malaysia, Malta, Mexico, Moldova, Morocco, Netherlands, New Zealand, Nigeria, Norway, Oman, Pakistan, Paraguay, Peru, Philippines, Poland, Portugal, Qatar, Romania, Russian Federation, Saudi Arabia, Serbia, Singapore, Slovak Republic, Slovenia, South Africa, Spain Sri Lanka, Sweden, Switzerland, Thailand, Trinidad Tobago, Tunisia, Turkey, Ukraine, United Kingdom, United States, Uruguay, Zambia.

- Europe: Slovenia, Romania, Czech Rep., Poland, Slovak Rep., Estonia, Lithuania, Portugal, Latvia, Bulgaria, Croatia, Greece, Hungary, Malta.
- Asia: Indonesia, Turkey.

We might say that, from a geographic point of view, there is a predominance from Central and East European countries and Latin American ones. We will now analyze the characteristics of the first group of countries. The variables for which the mean in the group is significantly different (lower in this case) than that of the entire sample are: market capitalization (V12), Stocks traded (V14), Gross savings (V7) and GDP/capita (V4). Considering the variables that individualize this group of countries, we can outline the following traits: capital market insufficiently developed (stocks traded, market capitalization), low financial power of the population (GDP/capita and gross saving). After exposing the characteristics for all the group of countries, we will analyze the position of the neighborhoods on the map and what important conclusions can be drawn.

Figure 2 – Self-Organizing Map of the economies in 2007

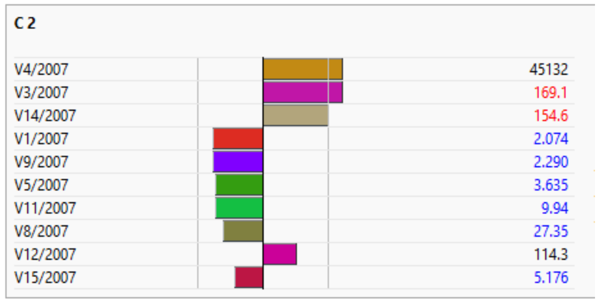


We continue our exposure for the so called clusters with the group on the left (the red one). The 21 countries included in this group are the following (based on the geographic criterion):

- Europe: Island, Switzerland, Sweden, Finland, UK, Spain, Denmark, Ireland, Netherlands, Germany, Austria, Belgium, Italy, Cyprus, France.
- Asia & Australia: Korea, Japan, Australia, New Zeeland.
- North America: USA, Canada.

In Figure 3 we have the characteristics of the group. We find that the designated countries register a value higher than the rest of the economies for the following variables: GDP/capita (V4), Domestic Credit (V3), Stocks traded (V14), and Market capitalization (V12). While the variables that register a lower average than that of the group are: Agriculture value added (V1), Inflation (V9), GDP growth (V5), Money growth (V11) and Industry value added (V8). We could say that this is the group of developed economies, with a mature financial market, however threatened by a stagnation of the economy (GDP growth, Money growth on a negative path).
We note that in the process of training the map, we used the standardized GDP and in the figures below, the initial values are presented. The software used was ViscoverySOMine, with the courtesy of the producers, in the purpose of academic research.

Figure 3 – Characteristics of the second group of countries

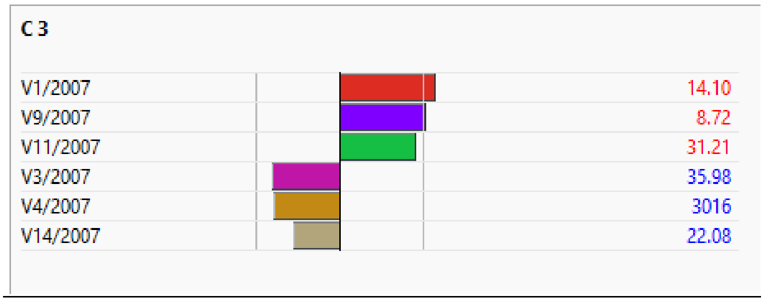


In the left part of the map, we also find two smaller subsets: Jordan and South Africa (left, lower corner) and Norway plus Singapore (left, upper cornet). Norway and Singapore are characterized by the highest values for Cash surplus (V2), Gross Savings (V7) and GDP per capita (V4), while Jordan and South Africa have the greatest market capitalization. Based on these extremes, it becomes easier to compare the countries from the red cluster considering their neighbors. We will return to this issue at the end of the section.
The third group of countries includes the following 15 economies (the yellow group on the right), classified on the geographical criterion:

- Europe: Serbia, Georgia, Moldova.
- Asia: Iran, Belarus, Russia, Pakistan, Sri Lanka.
- Africa: Egypt, Tunisia, Zambia, Cote d'Ivoire, Nigeria.
- Latin America: Rep. Dominican, Paraguay.

In Figure 4, we find that the variables with a higher average than that of the entire sample are: value added in the agriculture (V1), Inflation (V9), Money growth (V11), while the variables with a lower average than that of the sample are: Domestic Credit (V3), GDP per capita (V4) and Stocks traded (V14). This could mean that this group of countries are characterized by a moderate economic development and a low development of the financial market (Stocks traded, domestic credit).

Figure 4 – Characteristics of the third group of countries



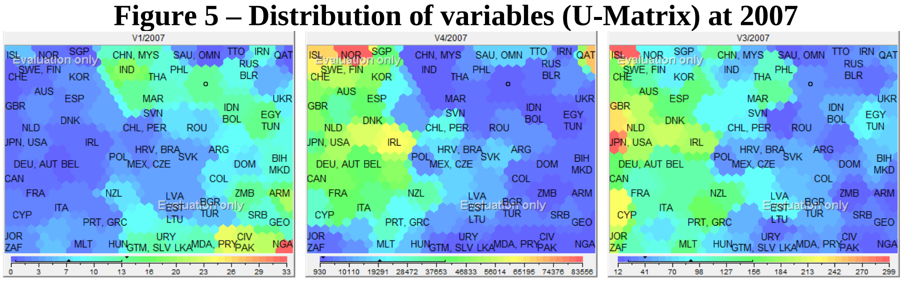
Still on the right side of the map we find Bosnia and Herzegovina, Macedonia and Armenia, grouped based on the very high levels for the unemployment in these economies. We also mention in this side of the map Ukraine, with an extreme high value for the level of non-performing loans.

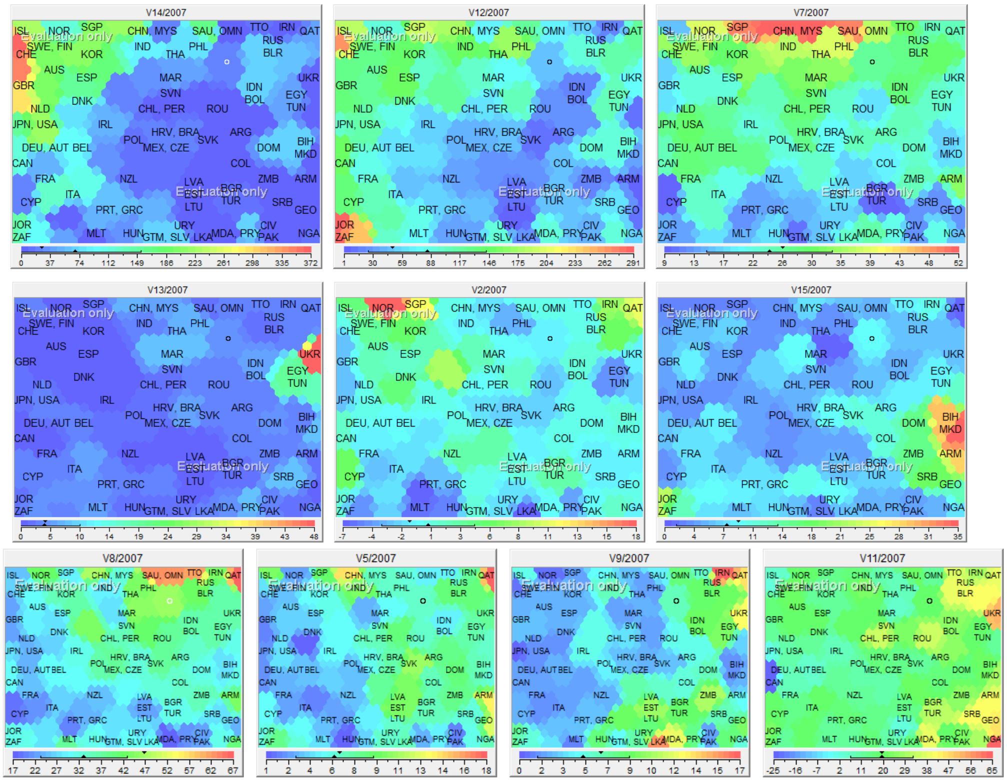
The last group of countries (upper side of the map, green) includes the nine following countries:

- Asia: China, Philippines, Saudi Arabia, Oman, Malaysia, India, Thailand.
- Africa: Trinidad and Tobago, Morocco.

This group is individualized by higher values for Gross Savings and Value Added in Industry, thus could be assimilated to the strongly industrialized countries. In Figure 5 we have the topology of the 13 variables included in the analysis on the map of countries – these are the so called U-matrixes.

Figure 5 – Distribution of variables (U-Matrix) at 2007



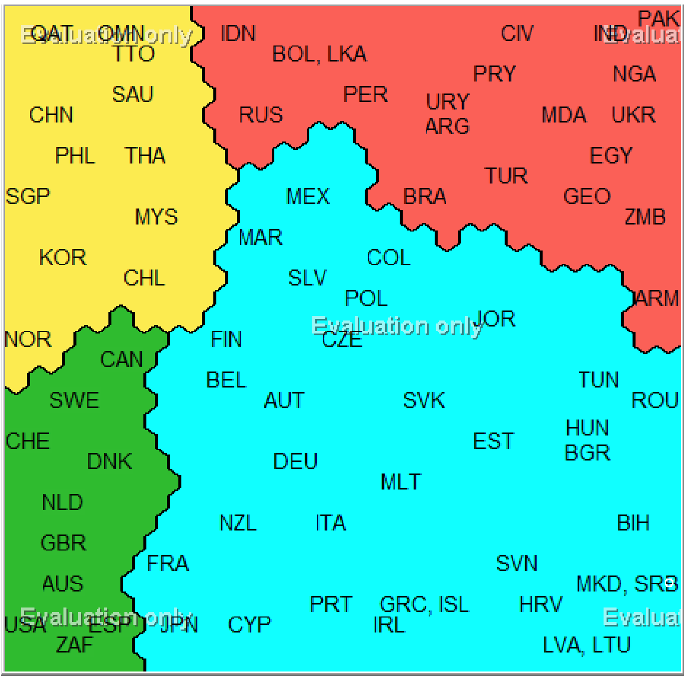


Based on Figure 5 and on the characteristics identified above, we can make a comparative analysis of the economies before the crisis (2007). Starting from the left side of the map, we can say that on this side we have concentrated the developed economies, as shown by the distribution of all macroeconomic variables (Figure 5). We can say that in 2007, the best situated economies were that of Sweden, Norway, Finland, USA, Great Britain, Netherlands, Canada. For Japan and Island, we notice the "red" zones on the Domestic credit, signaling very high levels of this variable. Ireland, Spain and Italy, on the other hand are closer to the "blue" group of countries (Cluster 1), meaning that they have characteristics similar to the countries situated in the center of the map. We observe that in the center of the map we have mostly the economies from South America and from Central Europe (Poland, Czech, Croatia, Slovenia) and a key characteristic, as seen from Figure 5, is the increased current account deficit at macroeconomic level. A subgroup of countries from the first cluster are more oriented to the right side of the map, that is to the countries with the lowest economic development from the sample. In this category we have the Baltic countries, Romania, Argentina, Colombia, Bulgaria, Turkey. These are the countries where we also register a low level of the development for the financial and moreover for the capital market. We also highlight the large non-performing loans rate for Egypt, Tunisia and Ukraine, while the top countries as for value added industry are situated at the top of the map (China, Malaysia, Oman, Saudi Arabia). This is the "picture" of the worlds' economies in the year preceding the global financial and economic crisis. In the next section we will analyze the mutations produced among the economies in the aftermath of the crisis.

5.3 Structural changes in the map at 2010

In this section of the paper we will analyze the self-organizing map in 2010, based on the same inputs used for 2007 (sample was reduced with four countries due to lack of data). In Figure 6 we have the topology of the economies on four distinct groups.

Figure 6 – Self-Organizing Map of the economies in 2010



The first group includes the following countries (the "blue" group in Figure 6):

- Mexico, Colombia, El Salvador.
- Poland, Slovenia, Czech Republic, Slovakia, Finland, Belgium, Austria, Germany, France, Portugal, Ireland, Greece, Island, Malta, Italy, Romania, Bulgaria, Hungary, Estonia, Croatia, Lithuania, Latvia, Macedonia, Serbia, Bosnia and Herzegovina, Cyprus
- New Zeeland, Japan, Morocco, Jordan, Tunisia

The main characteristic for this group of countries is the low level for the GDP growth. The “red” group of countries is individualized by high levels of inflation, money growth, agriculture value added and low levels of GDP/capita and Domestic Credit. Based on this descriptions, we can conclude that these are the countries which were the most affected by the Global crisis. Countries included in the “red” group are:

- Bolivia, Peru, Uruguay, Argentina, Paraguay, Brazil.
- Indonesia, India, Sri Lanka, Pakistan, Egypt, Turkey, Georgia, Russia, Armenia, Ukraine, Moldova.
- Nigeria, Zambia, Cote d’Ivoire.

On the right side of the map we find two sets of countries. Namely, the “yellow” and the “green” group. The “yellow” countries have high values for the value added in industry and for Savings. These countries are the following:

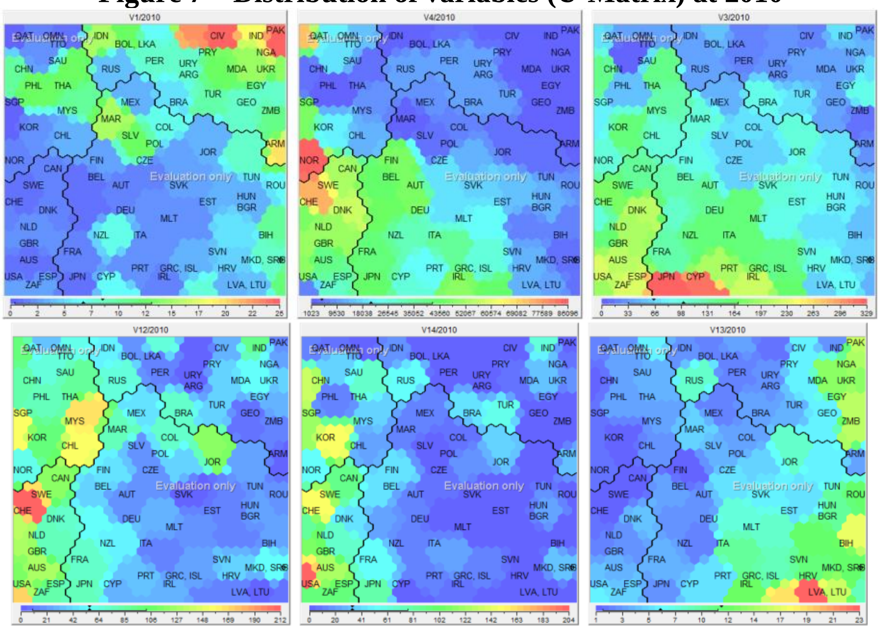
- Qatar, Oman, Saudi Arabia, Thailand, Philippine, Singapore, Korea, Malaysia.
- Norway, Chile, Trinidad Tobago.

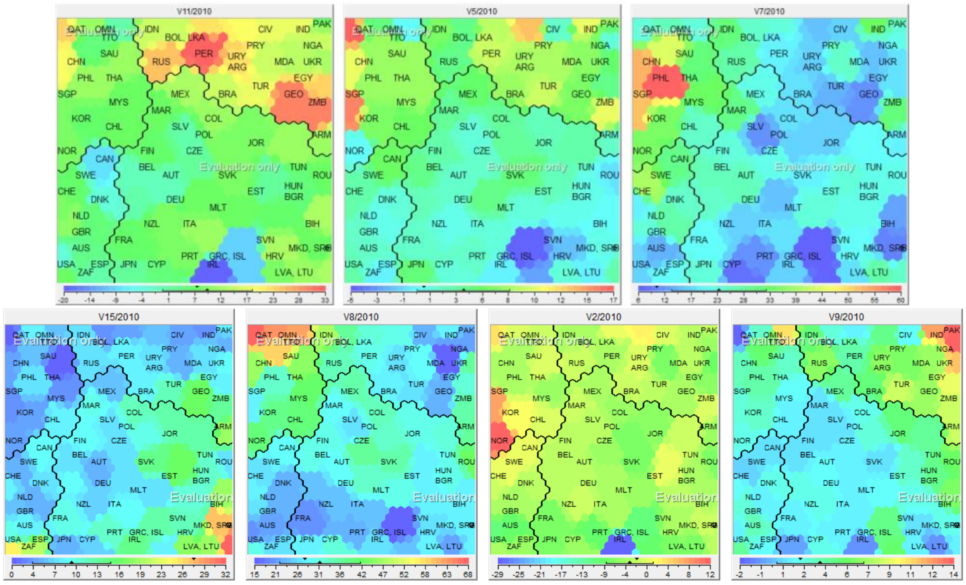
The last group of countries registers high values for the market capitalization, Stocks traded, Domestic credit and for the GDP/capita. The countries in this group are:

- Sweden, Denmark, Great Britain, Switzerland, Netherlands, Spain.
- Canada, USA, Australia, South Africa.

In Figure 7 below, we can observe the distribution of the variables in 2010 for the entire sample.

Figure 7 – Distribution of variables (U-Matrix) at 2010





6. Conclusions

In the present paper we have focused on two main objectives – observe the way the major events in 2007 affected a whatsoever “stable” map of the economies and focus on the key drivers that contributed to the overall performance of the economies during the crisis period, that is delimiting some “early warning signs” of crisis. We find that developed economies in the Western Europe have been as vulnerable as the emerging ones, in terms of macroeconomic indicators performance. The economies which that could be considered the less affected by the global crisis are the Asian markets and some Northern Europe economies. This result can be put on the account of the confidence in the financial markets of the Asian economies, which confirms the importance of the financial stability in the global economic environment.

The paper enriches the specialty literature of using self-organizing maps for characterizing crisis situations, by adding significant insight into the changes that took place on the “map” of economies after the global crisis from 2007, by identifying main groups of countries, their particularities and the distribution on the considered macroeconomic variables.

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