MAPPING OF STOCK EXCHANGES: AN ALTERNATIVE APPROACH

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Abstract

This paper uses the Self-organizing Maps (SOM) to develop a two-dimensional map based on seven market variables from 50 stock exchanges around the world for the period 2000/2012. Our intention is to classify them in distinctive groups and analyze their similarities, differences, and their dynamics. Each group is defined by the Euclidean distances between markets, and in the aggregate, they form three different zones. The resulted classification is recommended as a previous step for further studies of contagion and co-movement. We find that very few markets changed areas during the period. Mainly, the variables of several Asiatic and a two European markets, showed some improvements. Additionally, we note that the last financial crisis has heavily affected the largest markets, slowing down considerably their growth, while smaller exchanges have grown at a faster pace.

Keywords: mapping of stock exchanges, financial markets' cluster, self-organizing neural networks.

JEL codes: G15; F30; C63

I. Introduction

During the last years, a fruitful research area has been the study of the co-movements and contagion between stock exchanges of different as well as similar time zones. Within this framework, knowledge about the ties between the stock exchanges, their similarities as well as the level of connectivity may influence international dynamics.

In this paper, we draw a detailed map of 49 financial markets around the globe. This classification is done according to our method, which enables us to take into account the information contained in seven different market variables. The result is a map where we can observe visually the similarities between exchanges. With this methodology, we are also able to analyze the evolution of the stock exchanges during the period 2000/2012, and observe the impact of the booms and busts affecting the stock exchanges.

Different methods have been used to study the links between international stock markets. There are quite a few studies that relate contagion, correlations, herd behavior, diffusion, and common shocks with the financial markets, specifically, the stock exchanges in different zones and countries. Although all these notions mean different things, they are somehow related, due to specific factors, at least in the context of cause-effects relationships and co-movements[1] (Quinn & Voth, 2008).

The most used methodologies in this research arena are cross-market correlation coefficients, ARCH and GARCH models, and co-integration techniques, discriminant analysis, logistic and multiple regressions, ARIMA models, etc.[2]. Notwithstanding, our method, Self-Organizing Maps, allows analyzing databases of n-variables in two dimensions, and also helps to track the evolution of different components of the sample. Other methods that come from computational learning theory, like genetic algorithms, kernel classifiers, ant colony clustering, Bayesian networks, and fuzzy subspace clustering have been mainly applied to other fields, but almost

[1] The concept of financial contagion remains an elusive concern for researchers, with many definitions that limit its meaning. Moser (2003) gives us a summary of what does and does not mean. It traditionally has been related to bank runs, but nowadays it refers broadly speaking to the spread of a crisis in one country to another.

[2] Some examples are co-integration (Evans & McMillan, 2009), ultra metric spaces (Mantegna, 1999), graphical models (Abdelwahab & Amor, 2008), (Bessler & Yang, 2003), (Talih & Hengartner, 2005); GARCH models (Longin & Solnik, Is the correlation in international equity returns constant: 1960-1990?, 1995).

non to the stock markets. More related to our work is the paper by Fioramanti (2008) who uses neural networks to predict currency and debt crises. Kolarun (2010) also undertakes a multivariate comparative analysis of two distinctive groups of stock exchanges: Eastern and Western Europe. Sarlin and Peltonen (2013) use SOM to visualize the state of financial stability comparing their results with the ones obtained by Logit method. They concluded that the SOM performs equally well as a Logit model in predicting the financial crisis of 2007-2009.

However, to the best of our knowledge, none has made use of Artificial Neural Networks (ANNs) to study the behavior of a network of stock exchanges at a global scale, nor as a way to classify them according to their level of market linkages. ANNs have some advantages over more traditional classification schemes. We can define it as a non-linear data driven self-adaptive approach for modelling large amounts of raw databases with blanks and noise. Because of its adaptability, it can identify and learn in an iterative way about patterns between different complex data sets, specially, when these sets are quite noise and largely imprecise, as many stock exchanges from developing countries are. In addition, through a process of training, it can be used as a forecasting tool.

Our work is based in seven market variables to carry out the stock market classification map: Domestic Market Capitalization, Electronic Turnover Domestic and Foreign, Listings Domestic and Foreign, Market Capitalization of New Listings and Trading Days. The most relevant variable is Domestic Market Capitalization, followed by the Electronic Turnover and Market Capitalization of New Listings. The output consists of three different topological regions, according to the Euclidean distances among them.

The model differentiates the zones using colors. We find that the most important markets worldwide in terms of capitalization and volume traded are located in a R-zone (or Red) very distant apart from medium and small markets, and which are very different from each other. Small and some medium markets densely populate one of the areas of our model, the B-zone (or Blue), and some medium to large markets fill the zone in between, the G-zone (or Green).

Next, in order to study the evolution of the stocks exchanges, we have divided the sample into three non-overlapping periods: from 2000 to 2003, from 2004 to 2007 and from 2008 to 2012. Markets that move from one area to another are few, and they are mainly from Asia going from B to the middle G area. Markets in the R area are very stable, and just the Shanghai SE joined in during the last period, 2008/2012. It can also be checked that the crises 2008/2012 has affected at a high level the most capitalized markets which, on the other hand, were the ones that experienced higher growth in the variables studied during the 2004/2007 booming period.

In this paper we don't attempt to explain the causes of the changes in some Stock Exchanges, nor do we search into the possible contagion channels or levels. Our aim is to draw a map positioning different markets worldwide and studying their similarities as a departing point in order to study further the relationships among markets and the effects of their macroeconomic situations.

The rest of the paper is organized as follows. In section II we describe the sample used and explain the method, the Artificial Neural Networks (ANNs) model, followed, in section III, by its application to a set of 50 stock exchanges encompassing the world, and the analysis of the results. Finally, section IV concludes. References are at the end of the paper.

II. The Sample and the Method

A. The Sample

The database used in this study is the World Federation of Exchanges. The raw database covered 11 variables and 146 markets from 2000 to 2012. However, not all markets show data for each of the variables every year, and therefore, we filtered the database in order to find a balance between the number of variables and stock markets. We have used the variables that encompassed the largest number of markets, and the resulting dataset is composed by 7 variables for 49 different stock markets[3] (see Table 1).

[Insert Table 1 about here]

[3] This database does not discriminate between NYSE and Euronext before their merger in 2007.

For each market the variables studied are:

- Domestic Market Capitalization (companies admitted to listing only): DMC
- Electronic Turnover Domestic: ETD
- Electronic Turnover Foreign: ETF
- Listings Domestic: LD
- Listings Foreign: LF
- Market capitalization of new listings: MCNL
- Trading Days: TD

These variables define and characterize each market allowing us to draw comparisons and to study similarities. DMC will let us know the comprehensive value of the market, the size of the market. LD and LF are the number of companies listed on an exchange. LF is a key variable; it serves as a channel of contagion. ETD, ETF, MCNL give information about the level of activity in the market.[4]

We will find, in section III, when classifying the different stock exchanges according to these variables, that the more influencing variables are DMC, ETD and ETF, while the least one is TD.

For each variable, we have collected annual data from 2000 to 2012, a total of 13 years. We have divided the sample period in three non-overlapping periods: from 2000 to 2003, from 2004 to 2007 and from 2008 to 2012. With this study divided in three periods we can study the dynamics of the different markets and their evolution. We can also see how the prosperity and the rise of the years 2004/2007, and the crises of the years 2008/2012 have influenced the relative position of the markets. For each period, and for each market, we just use one figure per

[4] For more information about these variables, please consult: http://www.world-exchanges.org/statistics/statistics-definitions.

variable (the average of the corresponding years). Therefore, the model identifies each period for each market as an independent input.

Since we don't have data for all the years in all the markets, we have ensured that at least there is enough data for two out of the three sample periods. The final set of observations for each variable is 135. Therefore, our sample is composed by a total of 135 x 7 values.

We have normalized all these variables with logistic normalization procedure to avoid that the size of the variables affects the results. Scaling of variables is of special importance since, as we explain in the next section, our methodology uses Euclidean metric to measure distances between vectors. Logistic normalization ensures that all values are within the range [0 1] [5]. The transformation is more or less linear in the middle range and has a smooth nonlinearity at both ends which ensures that all values are within the range. The data is first scaled as in variance normalization: $\hat{x} = (x - \bar{x})/\sigma_x$. Then the logistic function applied: $x' = 1/\left(1 + e^{-\hat{x}}\right)$. The transformation parameters are the mean value $\bar{x}$ and standard deviation σ_x of the original values x, just like in the standard normalization procedure.

B. The Method: Self-organizing Neural Networks

Artificial neural networks were originated in the 1960s (Minsky & Papert, 1969) (Rosenblatt, 1958) (Wildrow & Hoff, 1960), but began to be used in the 90s (Hopfield, 1984) (Kohonen T. , Self-Organized formation of topologically correct feature maps, 1982) as an alternative to the prevailing Boolean logic computation (Vesanto & Alhoniemil, 2000).

Basically, there are two kinds of neural networks: supervised and self-organizing networks. The former are universal function "approximators" (Martín & Sanz, 1997) (Funahasi, 1989), used both to adjust functions and to predict results. The latter are data pattern classification networks. These kinds of networks discover similar patterns within a pool of data and group them based on such similarity (Martín & Sanz, 1997).

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[5] i.e., if one variable has values in the range of [0,…,1000] and another in the range of [0,…,1] the former will almost completely dominate the map organization because of its greater impact on the distances measured.

The first self-organizing networks were so-called "Competitive Networks", which include an input and an output layer. Each layer comprises a group of cells. Model inputs are introduced through the input layer cells. Each cell in the input layer is connected to each of the cells in the output layer by means of a number, called a synaptic weight. (Figure 1)

[Insert Figure 1 about here]

The goal of the network is to find out which cell in the output layer is most similar to the data introduced in the input layer. For this purpose, the model calculates the Euclidean distance between the values of the input layer cells and the values of the synaptic weights that connect the cells in the input layer to those of the output layer.

The cell that shows the least distance is the winner or Best-Matching Unit (BMU), and its synaptic weights are then adjusted using the learning rule, to approximate them to the data pattern. The result is that the Best Matching Unit has more possibilities of winning the competition in the next submission of input data; or fewer if the vector submitted is different.

Kohonen (1982, 1989, 1990, and 1997) introduced the neighborhood function to competitive networks, creating so-called Self-Organizing Feature Maps or SOMs. Kohonen's innovation consisted in incorporating to the winning cell a neighborhood function that defines the surrounding cells, altering the weights of both the winning cell and of other cells in the neighborhood thereof. The effect of introducing the neighborhood function is that cells close to the winning cell or BMU become attuned to the input patterns that have made the BMU the winner. Outside the neighborhood, cell weights remain unaltered. In order for an SOM-type self-organizing network to be able to classify it must have the capacity to learn. We divide the learning process into two stages:

1. Classification, to identify winning neurons and neighboring neurons.
2. Fine adjustment, to specialize winning neurons.

The mechanics of self-organizing maps begin by allocating random weights W_{ijk} to link the input layer and the output layer. Next an input data pattern, X(t), is introduced, and each neuron in the output layer calculates the similarity between its synaptic weight and the input vector, by means of the Euclidean Distance[6] represented in Equation 1.

Equation 1

$$d = \sqrt{\sum_{k=1}^{N} (W_{ijk} - X_k)^2}$$

The output network neuron that shows the least distance to the input pattern is the winning neuron, g*. The next step is to update the weights corresponding to the winning neuron (W_{ijk}) and its neighbors, using the following equation:

Equation 2

$$W_{ijk}(t+1) = W_{ijk}(t) + \alpha(t) \cdot h(|i - g^*|, t) \cdot (X_k(t) - W_{ijk}(t))$$

Where $\alpha(t)$ is learning term that takes values comprised between 0 and 1. Where the number of iterations exceeds 500, then $\alpha(t)$ tends to 0. Equation 3 is usually used to calculate $\alpha(t)$.

Equation 3

$$\alpha(t) = \alpha_0 + (\alpha_f - \alpha_0) \cdot \frac{t}{t_\alpha}$$

Where α_0 is the initial rate, α_f the final rates, which usually takes values amounting to 0.01, t is the current situation and $t_\alpha$is the maximum number of desired iterations.

The function $h(|i - g^*|, t)$ is the neighborhood function, and its size is reduced in each iteration. The neighborhood function depends on the distance and on the neighbor ratio. This function tells us that the neighborhood function decreases when the distance to the winning cell increases. The further away from the winning neuron, the smaller the cell's neighborhood function. It depends on the neighbor ratio R(t), which represents the size of the current neighborhood.

[6] There are other measurement criteria, such as the Manhattan distance or the Scalar product. However, the most commonly used is the Euclidean distance.

$h(|1-g*|,t) = f[R(t)]$

To calculate neighborhood Step functions or Mexican hat-type functions are used. The neighbor ratio R(t) decreases in time. Below is a commonly used equation that reduces the neighbor ratio in time:

Ecuación 4

$$R(t) = R_0 + (R_f - R_0) \cdot \frac{t}{t_R}$$

R_f is the final ratio, which takes a value equal to 1. Likewise, t_R is the number of iterations required to reach R_f.

In the fine adjustment stage, α is equal to 0.01, and the neighbor ratio is equal to 1. The number of iterations is proportional to the number of neurons, and separate from the number of inputs. Usually, between 50 and 100 iterations are sufficient.

The greater the number of identical patterns, the greater the number there will be of neurons that specialize in such pattern. The number of neurons specialized in recognizing an input pattern depends on the likelihood of such pattern. The resulting map therefore approaches a probability density function of the sensory space. The amount of neurons concentrated in a certain region show the greater likelihood of such patterns.

After declaring which is the BMU, the SOM's weight vectors are updated, and their topological neighbors move towards the input vector, thus reducing the distance. This adaptation generates a narrowing between the winning neuron and its topological neighbors. This is illustrated in **¡Error! No se encuentra el origen de la referencia.**, where the input vector is marked by an X. The winning neuron is marked with the acronym BMU. Observe how the winning neuron and its neighbors get closer to the input vector. This displacement is reduced to the extent that the distance from the BMU is greater.

[Insert Figure 2 about here]

Continuous lines and dotted lines respectively represent the situation before and after the update.

SOMs are especially useful to establish unknown relations between datasets. Datasets that do not have a known preset order can be classified by means of an SOM network. Many research papers in finance have made use of the SOM methodology. The work of Deboeck and Kohonen (1998) shows how this algorithm has led to many applications in physics and engineering, and also in finance. De Boldt et al (1996) applied SOM to simulate different scenarios of interest rates. Martin and Serrano (1995) analyzed the Spanish banking crisis. The Austrian Financial Market Authority includes the artificial neural networks as a method to model rating companies.

III. The Empirical Application

After normalization of variables, we initialize and make the map. The training is carried out in two phases: rough training with large neighborhood radius, and large learning rate and fine-tuning with small radius and learning rate.

In Figure 3 left we show the Unified Matrix map based on all the variables. This map visualizes distances between neighboring map units or cells, and helps to see the cluster structure of the map: high values of the Unified Matrix indicate a cluster border; uniform areas of low values indicate clusters themselves (Vesanto et al, 2000). This map is unrelated to the x-y Cartesian axes in which the vertical and horizontal ones refer to numerical values. In other words, a specific unit or cell has a meaning according to its color, not to its position in the map.

Each cell has a color indicating a Euclidean distance with its closest neighbor. The color bar shows the different distance values. Each unit gathers a set of markets with equal data, whereas the markets with similar data are located in the nearest neighborhood. Figure 3 right shows the overall result of our model: the markets distribution according to the similarities for each variable, this Figure 3 is related to Figure 5 where we identify the market and period in each cell.

To draw Figure 3 right out of the information in Figure 3 left, we use the Kmeans Clustering, which it is a means to group variables by using centroids. It is an easy method to do an unsupervised classification. The target is establishing centroids of different categories and after, classify by proximity. The first step is choosing k centroids in a random way but they must be far away each other's. The second step is classifying the different units depending on the nearest centroids. Then, the algorithm re-computes the position of the centroids, using the units that belong to each class. It repeats these iterations until the centroids do not move anymore. Finally, the Davies-Bouldin index is calculated for each clustering. (Jain and Dubes, 1988) (Davies and Bouldin 1979) (Vesanto and Alhoniemi, 2000) The result of apply k-means clustering is the right-map in figure 3, which it shows the different groups of this model.

[Insert Figure 3 about here]

The markets located within the same cell show the shortest Euclidean distance between their variables. As it can be observed in Figures 3 and 4, the map is divided in three different zones: Blue (B), Green (G) and Red (R). The Blue one gathers all the cells with the shortest Euclidean distance between them. The Green zone refers to the medium scale of Euclidean distance. The Red one collects the units with the longest distance between them and from the other ones (B and G).

Before identifying the market and period in each cell, we show the data distribution maps and the descriptive statistics for each one of the seven variables. The seven maps are shown next, in Figure 4, and represent different components linked by position: Each hexagon in all the maps corresponds to the same unit in all the maps, which means the same stock exchange in the same period. Each stock exchange (in each one out of the three periods) has been allocated to one cell according to the classification model and remains in that cell. The values of the components have been de-normalized so that the values shown on the color bar correspond to the original value range. In Figure 3 and later in Figure 5 we use the color code to define distances, however, in Figure 4, the color code represents the quantification of each variable. Thus, the blue range indicates a low level variable; the green range, the middle level; and the red range, the highest. Each component shows the values of one variable in each map unit.

As we can observe, the cells/markets in the R set show the highest values for all the variables, including the variables related to foreign markets: ETF and LF, so we may infer that these markets are the ones with more influence in and from other markets. In the G group we can find all the range of values for MCNL and TD, low values for ETF, and medium values for the rest. The B group shows low values for all variables, except the TD variable.

[Insert Figure 4 about here]

Relating Figure 4 to Figure 3 we appreciate that the most discriminant and influencing variable in our model is DMC. It can also be observed that ETD and LD lead to approximately the same classification. MCNL also corroborate the results of our model, indicating that the markets with higher level of activity are the ones placed in the R zone. The least influencing variable is TD, and this fact makes sense since this variable is of a very different nature, and as we will see in Table 2, there is almost no difference in this variable among the three groups.

Next, in Table 2 we show the descriptive statistics of the variables for the three groups resulting in the model: average, standard deviation, percentiles, minimum and maximum.

In this Table we observe the differences in the Euclidean distance between the three zones. The Euclidean distance among the markets in the R zone is almost six times that of the B group, and doubles that of the G group. So, these markets in the R group have more "personality", more differences among them. The lower Euclidean distance in the B group can be interpreted as a higher likeness among markets, that is, markets in this zone presents more similar values in the variables.

[Insert Table 2 about here]

We can appreciate that the average Domestic Market Capitalization for markets in the R group is more than twenty six times the average amount in the B group, and more than five times than in the G group. That results in large differences, but the most prominent difference among the three zones can be found for the ETF variable. ETF for the R zone is more than 79 times the B zone and 36 times the G zone. We find that the markets in the R group do have a really high level of Electronic Turnover Foreign in comparison to the rest of the markets. This means that markets at the R group have more presence of foreign companies, influencing other markets and serving as a channel of contagion in a much more pronounced way than markets in other areas.

Listing Domestic and Trading Days are the variables where, on average, least differences among groups can be found, so these are the least discriminant variables in our model. ETD in the R group is more than 57 times the B group.

Following, in Table 3 we show the total amount (aggregate) for each variable for each periods. These data will allow us to analyze the changes from period to period and measure the relative weight of each group. We note that during our total period of study, there has been a strong convergence of the B group towards the middle group (G), and after the 2007-2010 crises the differences among zones have been reduced. DMC has fallen during the period 2008-2012 for the R group, while it has remained steady for the G group, and has been increasing in the B group, pointing out that this group of small and more similar markets has been less affected by the 2008-2012 crises. We can also appreciate here that the R markets show a clear superiority according to the ETF and LF variables, pointing out that the exchanges in this group have more presence of foreign companies.

Nevertheless, ETD has been increasing steadily for the three groups, finally, the aggregate amount of LD is higher in the middle zone, and also MCNL during the prosperity period 2004/2007 is higher for the G zone.

[Insert table 3 about here]

In addition, the data in Table 3 allow us to measure the relative weight of each group. Some features are: the weights of the R group are falling for DMC and LD; DMC and the capitalization of new companies in the group G have dropped as well; however there is an increase in all variables for the B group, and this increase is notorious for the variables ETD and LD, indicating growing domestic markets and a higher level of activity during the last years of our study. All these facts suggest that the B group is evolving towards the G group, while the R and G group have been affected by the crisis and are not growing at the same pace.

Finally, in Table 4, the relative changes in variables from each of the three groups according to the Euclidean distances are shown. From the second to the third period, and for the R group, domestic capitalization has fallen 9%. There has been no variation of domestic listed companies during the same period, whereas the foreign ones have increased 16%, and the turnover of these foreign companies have increased more for this group (26%) than for the domestic group (16%). Pointing out, once more, that during the last crises period, markets in the R zone improved thanks to the foreign activity.

For the middle group, the period 2004/2007 was a blooming period; all variables experienced an astonishing increase, specially the ETF variable. As we shall check in Figure 5 this group is composed mainly by Asiatic markets (India, Taiwan, Korea, Hong Kong, Shezhen, Australia) and some European ones (Germany, Spain, and the Nordic markets -Nasdaq Copenhagen-). The period 2008/2012 was a quiet period with little development. DMC remained steady, while the capitalization of IPOs went down 49%.

The pattern followed by the B markets group was the opposite. Markets in the B group slowed down during the years 2004/2007 and progressed during the crises 2008/2012: all variables increased, in a range of 23% to 73%, with the only exception of the capitalization of IPOs that went up just by 2%. Again, this information suggests that the B group has been the least affected by the last crises; nevertheless, we see that this group did not experience the blossoming of the previous economic boom.

[Insert Table 4 about here]

Once studied the behavior of the different variables for the 3 groups during the thirteen years sample, we proceed to visualize each stock exchange in the map (Figure 5), in its corresponding cell. The cells in Figure 5 are numbered from 1 to 54 with the intention to help us in the analysis.

The R area covers the most capitalized and liquid stock markets of the world. It can be seen that NYSE-Euronext, NASDAQ and London Stock Exchange as well as the Tokyo market are located in this area during the three periods of study, and Shanghai during the last period. Only five markets out of the forty nine taking part in this study.

According to our model of Euclidean distances, the markets in this group are the ones that show bigger differences in the variables of study among them, and follow very different patterns.

Markets in group B are the smallest and follow more similar patterns. Within this area we find some European emerging markets (i.e., Budapest, Warsaw, Istanbul, etc.), some European developed markets (Athens, Wiener, Milan, Oslo…), some American markets (Buenos Aires, Colombia, Santiago, Mexican, etc.) and some Asiatic markets (Osaka, Malaysia,…). The only two African markets participating in our study are also located here (Egyptian and South African).

This B area is the one with the largest number of markets, and we can observe that some markets belonging to this group at the beginning of our sample period (2000-2003) have evolved towards the G group, mainly the Asiatic markets Hong Kong, Korea and Shenzhen. The German market also changed area, and it is especially notorious the case of the Nordic markets (Nasdaq Copenhagen) which evolved from cell 1, in the B area, to cell 15 in the G zone, showing a big rise in the period 2004/2007. We observe that the Spanish, Indian and Australian markets are also located in the G zone (Green area).

Quite different is the case of the Taiwanese market, which is the only one to step back to the B zone, probably pointing out to a decreasing leadership in comparison with other Asiatic partners.

[Insert a page with Figure 5 about here]

The main example of gained relevance is the Shanghai market, which was located in the G zone during the period 2000/2007 and finishes in the R group (2008/2012) showing an interesting change. It is noteworthy that just this market joined the R group during the sample period.

In this paper and with our model, the evolution observed is a relative one, it is in relation to the other markets in our sample, so we can conclude that the Asiatic stock exchanges have developed and have grown more than the European or American ones during the last nine years (2004-2012).

For a better understanding of Figure 5, we have separated the three groups and highlighted those stock exchanges that had experienced changes in the classifications. With red arrows we have indicated the stock markets that experienced evolution according to our model and changed groups. With a black arrow, we point the only market that stepped back from the G group into the B group, the Taiwan one.

Summarizing, we find that the B zone is the most populated area, with less differences among the variables characterizing the markets due to shorter Euclidean distances, and with higher homogeneous patterns of behavior. The R zone has more differences within its markets and more heterogeneous patterns. This fact can also be seen through the next figure.

The Figure 6 shows the units based on Euclidean distances with values below 0.2. The blue lines indicate the distances between cells. The left top area, where lay the B group, exhibits the highest level of connectivity.[7] This means that the stock markets in this group are more similar to each other. There is stock market similarity wherever we find a link.

[Insert Figure 6 about here]

We find clearly two different areas in the G group. On the left hand side, we can appreciate a high connectivity between cells 6, 7, 8, 9, 15, 16 and 17. Here we find some European and Asiatic markets (i.e., Germany, India, Spain, Korea, Australia). On the right hand side, we find just cells 50 and 42 connected. These are Asiatic markets (i.e., Hong Kong, Shenzhen), the Canadian, and some North American markets (TMX group).

[7] Be aware that here we speak from the classification method point of view and not from a financial contagion perspective.

Connectivity in the R area is the lowest, with the exception of Shanghai and Tokyo (cell 52). These markets follow more differentiated patterns, and we can even talk about a different "personality" and characterization of these markets.

Finally, in Figure 7 we visualize in a 3-D graph the distribution of the 54 cells that compose the map. Through this graph, we can easily understand that the B Group area is the most densely populated. The markets belonging to the B group are the most similar, with shortest Euclidean distance and with a higher degree of connectivity. In this figure, it can also be clearly appreciated the distance between the different groups.

[Insert Figure 7 about here]

IV. Conclusions

In this paper, we map 49 stock exchanges using a methodology that enables us to classify them according to seven variables. This methodology, Self-organizing Neural Net Maps, compiles the information into a 2-D map, visual and intuitive. It also allows us to follow the evolution of the different stock exchanges. The classification is carried out using patterns of likeness, and, in this sense, the map let us to identify similarities and differences between stock exchanges. Since the method is based on Euclidean distances, we can also appreciate how different apart are the markets.

There are some other classificatory methods that come from a large array of fields: artificial intelligence, computational theory, and operations research that have been applied to the financial markets. Nevertheless, our model is the first one to accomplish a dynamic classification of 49 stock exchanges taking into account a considerable number of variables and, as a result, we can visualize the evolution of global exchanges through three distinctive groups or areas.

The results allow us to identify three different areas. One area, the B group, (or Blue group according to the color classification) is densely populated and the markets located there present a lot of similarities, although they belong to different geographical areas. We find here some small and middle markets like some European emerging markets, European developed markets, American markets, and Asiatic markets. The only two African markets participating in our study are also located here (El Cairo and Johannesburg markets).

The R group (or Red group) is very sparsely populated, and with less similarities. The fact that markets are more isolated from each other is a sign of their own idiosyncrasy, or even we could say about their own personality: London SE, Nasdaq OMX, NYSE-Euronext and Tokyo belong to this group. During the thirteen-year period that covers this study, only the Shanghai SE joined the group.

The mid-range group G (or Green group) presents a higher level of connectivity than markets in the R group, but less similarities than markets in the B one. We can observe that the Spanish, Indian and Australian markets are located in this zone. We can also detect that, together with two European markets, the German and the Nasdaq Copenhagen SEs, and some Asiatic markets moved to this area during the last ten years, mainly, Shenzhen, Korea, and Hong Kong -while the Taiwanese market stepped back to the B zone-. The monitoring of the markets' dynamics is one of the strengths of the proposed model.

Out of the seven variables used to map the 49 markets, we find that the key variables are Domestic Market Capitalization and Volume traded. We find that a big difference between markets in the R area and the other two groups is the turnover and listing of foreign companies. This fact establishes a channel of contagion for and from the different markets. However, we do not perform a contagion study nor do we go into details about the causes of the different patterns and evolution followed by the markets, that is, whether these are related to macroeconomic variables, commerce, legal or political situations.

Finally, we note that the financial crises of 2008/2012 have had, overall, a higher impact in the G and R groups than in the B group. Also, emerging and smaller capitalization markets have grown at a faster pace in the same period.

IV. References

Abdelwahab, A., & Amor, O. (2008). The analysis of the interdependence structure in International financial markets by graphical models. International research journal of finance and economics (15), 1450-2887.

Bessler, D., & Yang, J. (2003). The structure of interdependence in international stock markets. Journal of international money and finance (22), 261-287.

Davies, D.L., Bouldin, D.W. (1979) A Cluster Separation Measure, IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. PAMI-1, no. 2, pp. 224-227.

De Boldt, E., Grégoire, P., & Cottrell, M. (1996). Simulating interest rate structure evolution on a long term horizont. A Kohonen map application. Pasadena: Californian Institute of Technology.

Deboeck, G., & Kohonen, T. (1998). Visual Explorations in Finance with Self-Organizing Maps. Berlin: Springer-Verlag.

Evans, T., & McMillan, D. (2009). Financial co-movement and correlation: evidence from 33 international stock market indices. International Journal of Banking, Accounting and Finance, 1(3), 215-241.

Fioramanti, M. (2008). Predicting Sovereign Debt Crises using Artificial Neural Networks; A Comparative Approach, *Journal of Financial Stability*, 4(2): 149-164.

Funahasi, K. (1989). On the approximate realization of continuous mapping by neural networks. Neural Networks (2), 183-192.

Hopfield, J. (1984). Neural networks and physical system with emergent collective computational propiertie like those of two-state neurons. In N. A. Sciences (Ed.). (pp. 2254-2258). Washington: National Acedemy of Sciences.

Jain, A.K., Dubes, R.C. (1988) Algorithms for Clustering Data, Prentice Hall, pp. 96-101.

Kohonen, T. (1982). Self-Organized formation of topologically correct feature maps. Biological Cybernetics (43), 59-69.

Kohonen, T. (1989). Self-Organization and Associative Memory. Berlín: Springer-Verlag.

Kohonen, T. (1990). The Self-organizing Map. Proceeding of the IEEE, 9(78), 1464-1480.

Kohonen, T. (1997). Introduction to SOM Toolbox. Helsinki: EET DST.

Kolarun, J. (2010): "Multivariate Comparative Analysis of Stock Exchanges: The European Perspective", in Fink et al, (eds) "Advances in Data Analysis, Data Handling and Business Intelligence". Studies in Classification, Data Analysis, and Knowledge Organization, pp. 461-469, Springer-Verlag Berlin Heidelberg.

Mantegna, R. (1999). Hierarchical structure in financial markets. The European Physical Journal B (11), 193-197.

Martín, B., & Sanz, A. (1997). Redes Neuronales y Sistemas Borrosos. Madrid: Ra-MA.

Martín, B., & Serrano, C. (1995). Self-organizing Neural Networks: The financial state of Spanish companies. In Neural Networks in Capital Markets (pp. 341-358). Chichester: Wiley.

Minsky, M., & Papert, S. (1969). Perceptrons. Cambridge: MIT Press.

Moser, T. (2003): What is International Financial Contagion?, *International Finance*, vol. 6, issue 2, pag. 157-178.

Quinn, D., & Voth, H.-J. (2008). A century of global equity market correlations. American Economic Review: Papers & Proceedings, 98(2), 535-540.

Rosenblatt, F. (1958). The Perceptrons. A probabilistic model for information storage and organization in the brain. Psychological Review, 65(6), 386-408.

Sarlin, P. Peltonen, T. (2013). Mapping the State of Finance Stability. Journal of International Financial Markets, Institutions and Money. 26 46-76.

Talih, M., & Hengartner, N. (2005). Structural learning with time-varying components: tracking the cross-section of financial time series. Journal of Royal Statistical Society, 67(3), 321-341.

Vesanto, J., & Alhoniemil, E. (2000). Clustering of the Self-Organizing Map. IEEE Transactions on Neural Networks, 11(3), 586-600.

Vesanto, J., Himberg, J., Alhoniemi, E., & Parhankangas, J. (2000). SOM Toolbox for Matlab 5. Helsinki: Helsinky University of Technology.

Wildrow, B., & Hoff, M. (1960). Adaptive switching circuits. (pp. 96-104). New York: IRE.

Annex for referees

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27
1	0,0	0,0	0,1	0,1	0,2	0,2	0,3	0,5	0,6	0,0	0,0	0,0	0,1	0,2	0,2	0,3	0,5	0,6	0,1	0,1	0,1	0,1	0,2	0,2	0,3	0,6	0,7
2	0,0	0,0	0,1	0,1	0,2	0,2	0,3	0,4	0,5	0,0	0,1	0,0	0,1	0,2	0,2	0,3	0,5	0,5	0,1	0,1	0,1	0,1	0,1	0,2	0,3	0,6	0,7
3	0,1	0,1	0,0	0,1	0,2	0,2	0,3	0,4	0,5	0,1	0,1	0,0	0,1	0,1	0,2	0,3	0,4	0,5	0,1	0,2	0,1	0,1	0,1	0,2	0,3	0,6	0,7
4	0,1	0,1	0,1	0,0	0,1	0,1	0,2	0,4	0,5	0,1	0,1	0,1	0,1	0,1	0,1	0,2	0,4	0,5	0,2	0,2	0,1	0,1	0,1	0,2	0,2	0,6	0,6
5	0,2	0,2	0,2	0,1	0,0	0,1	0,2	0,4	0,5	0,2	0,2	0,2	0,1	0,1	0,2	0,2	0,4	0,5	0,2	0,3	0,2	0,2	0,2	0,2	0,2	0,5	0,6
6	0,2	0,2	0,2	0,1	0,1	0,0	0,1	0,3	0,4	0,3	0,2	0,2	0,1	0,1	0,1	0,1	0,3	0,4	0,3	0,3	0,2	0,2	0,1	0,1	0,1	0,4	0,5
7	0,3	0,3	0,3	0,2	0,2	0,1	0,0	0,2	0,3	0,3	0,3	0,3	0,2	0,2	0,1	0,1	0,2	0,3	0,4	0,4	0,3	0,3	0,2	0,1	0,1	0,4	0,4
8	0,5	0,4	0,4	0,4	0,4	0,3	0,2	0,0	0,1	0,5	0,4	0,4	0,4	0,3	0,3	0,2	0,1	0,1	0,5	0,5	0,4	0,4	0,3	0,2	0,2	0,3	0,3
9	0,6	0,5	0,5	0,5	0,5	0,4	0,3	0,1	0,0	0,6	0,5	0,5	0,5	0,4	0,4	0,3	0,2	0,1	0,6	0,6	0,5	0,5	0,4	0,4	0,3	0,4	0,4
10	0,0	0,0	0,1	0,1	0,2	0,3	0,3	0,5	0,6	0,0	0,0	0,1	0,1	0,2	0,2	0,3	0,5	0,6	0,1	0,1	0,1	0,1	0,2	0,2	0,3	0,6	0,7
11	0,0	0,1	0,1	0,1	0,2	0,2	0,3	0,4	0,5	0,0	0,0	0,1	0,1	0,2	0,2	0,3	0,5	0,5	0,0	0,1	0,0	0,1	0,1	0,2	0,3	0,6	0,7
12	0,0	0,0	0,0	0,1	0,2	0,2	0,3	0,4	0,5	0,1	0,1	0,0	0,1	0,1	0,2	0,3	0,4	0,5	0,1	0,1	0,1	0,1	0,1	0,2	0,3	0,6	0,7
13	0,1	0,1	0,1	0,1	0,1	0,1	0,2	0,4	0,5	0,1	0,1	0,1	0,0	0,1	0,1	0,2	0,4	0,5	0,1	0,1	0,1	0,1	0,1	0,1	0,2	0,5	0,6
14	0,2	0,2	0,1	0,1	0,1	0,1	0,2	0,3	0,4	0,2	0,2	0,1	0,1	0,0	0,1	0,2	0,3	0,4	0,2	0,2	0,2	0,2	0,1	0,1	0,2	0,5	0,6
15	0,2	0,2	0,2	0,1	0,2	0,1	0,1	0,3	0,4	0,2	0,2	0,2	0,1	0,1	0,0	0,1	0,3	0,4	0,3	0,3	0,2	0,2	0,1	0,1	0,1	0,5	0,5
16	0,3	0,3	0,3	0,2	0,2	0,1	0,1	0,2	0,3	0,3	0,3	0,3	0,2	0,2	0,1	0,0	0,2	0,3	0,3	0,3	0,3	0,2	0,2	0,1	0,0	0,4	0,4
17	0,5	0,5	0,4	0,4	0,4	0,3	0,2	0,1	0,2	0,5	0,5	0,4	0,4	0,3	0,3	0,2	0,0	0,1	0,5	0,5	0,4	0,4	0,3	0,3	0,2	0,2	0,3
18	0,6	0,5	0,5	0,5	0,5	0,4	0,3	0,1	0,1	0,6	0,5	0,5	0,5	0,4	0,4	0,3	0,1	0,0	0,6	0,6	0,5	0,5	0,4	0,3	0,3	0,3	0,3
19	0,1	0,1	0,1	0,2	0,2	0,3	0,4	0,5	0,6	0,1	0,0	0,1	0,1	0,2	0,3	0,3	0,5	0,6	0,0	0,0	0,1	0,1	0,2	0,2	0,3	0,7	0,7
20	0,1	0,1	0,2	0,2	0,3	0,3	0,4	0,5	0,6	0,1	0,1	0,1	0,1	0,2	0,3	0,3	0,5	0,6	0,0	0,0	0,1	0,1	0,2	0,2	0,3	0,6	0,7
21	0,1	0,1	0,1	0,1	0,2	0,2	0,3	0,4	0,5	0,1	0,0	0,1	0,1	0,2	0,2	0,3	0,4	0,5	0,1	0,1	0,0	0,1	0,1	0,2	0,3	0,6	0,7
22	0,1	0,1	0,1	0,1	0,2	0,2	0,3	0,4	0,5	0,1	0,1	0,1	0,1	0,2	0,2	0,2	0,4	0,5	0,1	0,1	0,1	0,0	0,1	0,1	0,2	0,5	0,6
23	0,2	0,1	0,1	0,1	0,2	0,1	0,2	0,3	0,4	0,2	0,1	0,1	0,1	0,1	0,1	0,2	0,3	0,4	0,2	0,2	0,1	0,1	0,0	0,1	0,2	0,5	0,6
24	0,2	0,2	0,2	0,2	0,2	0,1	0,1	0,2	0,4	0,2	0,2	0,2	0,1	0,1	0,1	0,1	0,3	0,3	0,2	0,2	0,2	0,1	0,1	0,0	0,1	0,5	0,5
25	0,3	0,3	0,3	0,2	0,2	0,1	0,1	0,2	0,3	0,3	0,3	0,3	0,2	0,2	0,1	0,0	0,2	0,3	0,3	0,3	0,3	0,2	0,2	0,1	0,0	0,4	0,4
26	0,6	0,6	0,6	0,6	0,5	0,4	0,4	0,3	0,4	0,6	0,6	0,6	0,5	0,5	0,5	0,4	0,2	0,3	0,7	0,6	0,6	0,5	0,5	0,5	0,4	0,0	0,1
27	0,7	0,7	0,7	0,6	0,6	0,5	0,4	0,3	0,4	0,7	0,7	0,7	0,6	0,6	0,5	0,4	0,3	0,3	0,7	0,7	0,7	0,6	0,6	0,5	0,4	0,1	0,0
28	0,2	0,2	0,2	0,2	0,3	0,3	0,4	0,5	0,6	0,1	0,1	0,2	0,2	0,3	0,3	0,4	0,5	0,6	0,1	0,0	0,1	0,1	0,2	0,3	0,4	0,7	0,7
29	0,2	0,2	0,3	0,3	0,3	0,4	0,4	0,5	0,6	0,2	0,2	0,2	0,2	0,3	0,3	0,4	0,5	0,6	0,1	0,1	0,1	0,2	0,3	0,3	0,4	0,7	0,7
30	0,1	0,1	0,2	0,2	0,3	0,3	0,3	0,4	0,5	0,1	0,1	0,2	0,2	0,2	0,3	0,3	0,4	0,5	0,1	0,0	0,1	0,1	0,2	0,2	0,3	0,6	0,7
31	0,2	0,2	0,2	0,2	0,3	0,3	0,3	0,4	0,5	0,2	0,2	0,2	0,2	0,2	0,2	0,3	0,4	0,5	0,1	0,1	0,1	0,1	0,2	0,2	0,3	0,6	0,6
32	0,2	0,2	0,2	0,2	0,2	0,2	0,2	0,3	0,4	0,2	0,2	0,2	0,1	0,2	0,2	0,2	0,3	0,4	0,2	0,2	0,1	0,1	0,1	0,1	0,2	0,5	0,5
33	0,3	0,3	0,3	0,3	0,3	0,3	0,2	0,2	0,3	0,3	0,3	0,3	0,3	0,3	0,2	0,2	0,2	0,3	0,3	0,3	0,3	0,2	0,2	0,2	0,2	0,4	0,4
34	0,4	0,4	0,4	0,4	0,3	0,3	0,2	0,2	0,3	0,4	0,4	0,4	0,3	0,3	0,3	0,2	0,1	0,2	0,4	0,4	0,4	0,3	0,3	0,2	0,2	0,2	0,3
35	0,9	0,9	0,9	0,8	0,8	0,7	0,6	0,6	0,6	0,9	0,9	0,8	0,8	0,8	0,7	0,7	0,5	0,5	0,9	0,9	0,8	0,8	0,8	0,7	0,6	0,3	0,3
36	1,0	1,0	1,0	0,9	0,9	0,8	0,7	0,7	0,7	1,0	1,0	1,0	0,9	0,9	0,8	0,8	0,6	0,6	1,0	1,0	0,9	0,9	0,9	0,8	0,7	0,4	0,4
37	0,2	0,3	0,3	0,3	0,4	0,4	0,5	0,5	0,6	0,2	0,2	0,3	0,3	0,4	0,4	0,4	0,6	0,6	0,2	0,1	0,2	0,2	0,3	0,3	0,4	0,7	0,8
38	0,3	0,3	0,4	0,4	0,4	0,5	0,5	0,6	0,6	0,3	0,3	0,3	0,3	0,4	0,4	0,5	0,6	0,7	0,2	0,2	0,3	0,3	0,4	0,4	0,5	0,7	0,8
39	0,2	0,2	0,3	0,3	0,3	0,4	0,4	0,5	0,6	0,2	0,2	0,2	0,2	0,3	0,3	0,4	0,5	0,6	0,2	0,1	0,2	0,2	0,3	0,3	0,4	0,7	0,7
40	0,3	0,3	0,3	0,3	0,4	0,4	0,4	0,4	0,5	0,3	0,2	0,3	0,3	0,3	0,3	0,4	0,4	0,5	0,2	0,2	0,2	0,2	0,3	0,3	0,4	0,6	0,6
41	0,3	0,3	0,3	0,3	0,3	0,3	0,3	0,3	0,4	0,3	0,3	0,3	0,2	0,3	0,3	0,3	0,3	0,4	0,3	0,2	0,2	0,2	0,2	0,2	0,3	0,5	0,5
42	0,5	0,5	0,5	0,5	0,5	0,4	0,4	0,3	0,4	0,5	0,5	0,5	0,4	0,4	0,4	0,4	0,3	0,3	0,5	0,5	0,4	0,4	0,4	0,3	0,3	0,4	0,4
43	0,6	0,6	0,6	0,6	0,5	0,5	0,4	0,3	0,4	0,6	0,6	0,6	0,5	0,5	0,5	0,4	0,3	0,3	0,6	0,6	0,5	0,5	0,5	0,4	0,4	0,2	0,3
44	0,9	0,9	0,8	0,8	0,8	0,7	0,6	0,6	0,6	0,9	0,9	0,8	0,8	0,8	0,7	0,7	0,5	0,5	0,9	0,8	0,8	0,8	0,7	0,7	0,6	0,3	0,3
45	1,1	1,1	1,1	1,0	1,0	0,9	0,9	0,8	0,8	1,1	1,1	1,1	1,0	1,0	0,9	0,9	0,8	0,8	1,1	1,1	1,1	1,0	1,0	0,9	0,9	0,5	0,5
46	0,3	0,4	0,4	0,4	0,5	0,5	0,5	0,6	0,7	0,3	0,3	0,4	0,4	0,4	0,5	0,5	0,6	0,7	0,3	0,2	0,3	0,3	0,4	0,4	0,5	0,8	0,8
47	0,4	0,4	0,5	0,5	0,5	0,5	0,6	0,6	0,7	0,4	0,4	0,4	0,4	0,5	0,5	0,6	0,7	0,7	0,3	0,3	0,4	0,4	0,5	0,5	0,6	0,8	0,8
48	0,4	0,4	0,4	0,4	0,5	0,5	0,5	0,6	0,7	0,3	0,3	0,4	0,4	0,4	0,5	0,5	0,6	0,7	0,3	0,3	0,3	0,3	0,4	0,4	0,5	0,7	0,8
49	0,4	0,4	0,4	0,4	0,5	0,5	0,5	0,5	0,6	0,4	0,4	0,4	0,4	0,4	0,5	0,5	0,5	0,6	0,3	0,3	0,3	0,3	0,4	0,4	0,5	0,6	0,7
50	0,5	0,5	0,5	0,5	0,5	0,4	0,4	0,4	0,4	0,4	0,4	0,4	0,4	0,4	0,4	0,4	0,4	0,4	0,4	0,4	0,4	0,3	0,4	0,3	0,4	0,5	0,5
51	0,6	0,6	0,6	0,6	0,6	0,5	0,5	0,4	0,4	0,6	0,6	0,6	0,5	0,5	0,5	0,5	0,4	0,4	0,6	0,5	0,5	0,5	0,5	0,4	0,4	0,4	0,4
52	0,7	0,7	0,7	0,6	0,6	0,6	0,5	0,4	0,4	0,7	0,6	0,6	0,6	0,6	0,5	0,5	0,4	0,4	0,6	0,6	0,6	0,5	0,5	0,5	0,5	0,3	0,3
53	0,8	0,8	0,8	0,7	0,7	0,7	0,6	0,5	0,5	0,8	0,8	0,8	0,7	0,7	0,7	0,6	0,5	0,5	0,8	0,7	0,7	0,7	0,7	0,6	0,6	0,3	0,3
54	1,0	1,0	1,0	1,0	0,9	0,9	0,8	0,8	0,8	1,0	1,0	1,0	0,9	0,9	0,9	0,8	0,7	0,7	1,0	1,0	1,0	0,9	0,9	0,9	0,8	0,5	0,5

	28	29	30	31	32	33	34	35	36	37	38	39	40	41	42	43	44	45	46	47	48	49	50	51	52	53	54
1	0,2	0,2	0,1	0,2	0,2	0,3	0,4	0,9	1,0	0,2	0,3	0,2	0,3	0,3	0,5	0,6	0,9	1,1	0,3	0,4	0,4	0,4	0,5	0,6	0,7	0,8	1,0
2	0,2	0,2	0,1	0,2	0,2	0,3	0,4	0,9	1,0	0,3	0,3	0,2	0,3	0,3	0,5	0,6	0,9	1,1	0,4	0,4	0,4	0,4	0,5	0,6	0,7	0,8	1,0
3	0,2	0,3	0,2	0,2	0,2	0,3	0,4	0,9	1,0	0,3	0,4	0,3	0,3	0,3	0,5	0,6	0,8	1,1	0,4	0,5	0,4	0,4	0,5	0,6	0,7	0,8	1,0
4	0,2	0,3	0,2	0,2	0,2	0,3	0,4	0,8	0,9	0,3	0,4	0,3	0,3	0,3	0,5	0,6	0,8	1,0	0,4	0,5	0,4	0,4	0,5	0,6	0,6	0,7	1,0
5	0,3	0,3	0,3	0,3	0,2	0,3	0,3	0,8	0,9	0,4	0,4	0,3	0,4	0,3	0,5	0,5	0,8	1,0	0,5	0,5	0,5	0,5	0,5	0,6	0,6	0,7	0,9
6	0,3	0,4	0,3	0,3	0,2	0,3	0,3	0,7	0,8	0,4	0,5	0,4	0,4	0,3	0,4	0,5	0,7	0,9	0,5	0,5	0,5	0,5	0,4	0,5	0,6	0,7	0,9
7	0,4	0,4	0,3	0,3	0,2	0,2	0,2	0,6	0,7	0,5	0,5	0,4	0,4	0,3	0,4	0,4	0,6	0,9	0,5	0,6	0,5	0,5	0,4	0,5	0,5	0,6	0,8
8	0,5	0,5	0,4	0,4	0,3	0,2	0,2	0,6	0,7	0,5	0,6	0,5	0,4	0,3	0,3	0,3	0,6	0,8	0,6	0,6	0,6	0,5	0,4	0,4	0,4	0,5	0,8
9	0,6	0,6	0,5	0,5	0,4	0,3	0,3	0,6	0,7	0,6	0,6	0,6	0,5	0,4	0,4	0,4	0,6	0,8	0,7	0,7	0,7	0,6	0,4	0,4	0,4	0,5	0,8
10	0,1	0,2	0,1	0,2	0,2	0,3	0,4	0,9	1,0	0,2	0,3	0,2	0,3	0,3	0,5	0,6	0,9	1,1	0,3	0,4	0,3	0,4	0,4	0,6	0,7	0,8	1,0
11	0,1	0,2	0,1	0,2	0,2	0,3	0,4	0,9	1,0	0,2	0,3	0,2	0,2	0,3	0,5	0,6	0,9	1,1	0,3	0,4	0,3	0,4	0,4	0,6	0,6	0,8	1,0
12	0,2	0,2	0,2	0,2	0,2	0,3	0,4	0,8	1,0	0,3	0,3	0,2	0,3	0,3	0,5	0,6	0,8	1,1	0,4	0,4	0,4	0,4	0,4	0,6	0,6	0,8	1,0
13	0,2	0,2	0,2	0,2	0,1	0,3	0,3	0,8	0,9	0,3	0,3	0,2	0,3	0,2	0,4	0,5	0,8	1,0	0,4	0,4	0,4	0,4	0,4	0,5	0,6	0,7	0,9
14	0,3	0,3	0,2	0,2	0,2	0,3	0,3	0,8	0,9	0,4	0,4	0,3	0,3	0,3	0,4	0,5	0,8	1,0	0,4	0,5	0,4	0,4	0,4	0,5	0,6	0,7	0,9
15	0,3	0,3	0,3	0,2	0,2	0,2	0,3	0,7	0,8	0,4	0,4	0,3	0,3	0,3	0,4	0,5	0,7	0,9	0,5	0,5	0,5	0,5	0,4	0,5	0,5	0,7	0,9
16	0,4	0,4	0,3	0,3	0,2	0,2	0,2	0,7	0,8	0,4	0,5	0,4	0,4	0,3	0,4	0,4	0,7	0,9	0,5	0,6	0,5	0,5	0,4	0,5	0,5	0,6	0,8
17	0,5	0,5	0,4	0,4	0,3	0,2	0,1	0,5	0,6	0,6	0,6	0,5	0,4	0,3	0,3	0,3	0,5	0,8	0,6	0,7	0,6	0,5	0,4	0,4	0,4	0,5	0,7
18	0,6	0,6	0,5	0,5	0,4	0,3	0,2	0,5	0,6	0,6	0,7	0,6	0,5	0,4	0,3	0,3	0,5	0,8	0,7	0,7	0,7	0,6	0,4	0,4	0,4	0,5	0,7
19	0,1	0,1	0,1	0,1	0,2	0,3	0,4	0,9	1,0	0,2	0,2	0,2	0,2	0,3	0,5	0,6	0,9	1,1	0,3	0,3	0,3	0,3	0,4	0,6	0,6	0,8	1,0
20	0,0	0,1	0,0	0,1	0,2	0,3	0,4	0,9	1,0	0,1	0,2	0,1	0,2	0,2	0,5	0,6	0,8	1,1	0,2	0,3	0,3	0,3	0,4	0,5	0,6	0,7	1,0
21	0,1	0,1	0,1	0,1	0,1	0,3	0,4	0,8	0,9	0,2	0,3	0,2	0,2	0,2	0,4	0,5	0,8	1,1	0,3	0,4	0,3	0,3	0,4	0,5	0,6	0,7	1,0
22	0,1	0,2	0,1	0,1	0,1	0,2	0,3	0,8	0,9	0,2	0,3	0,2	0,2	0,2	0,4	0,5	0,8	1,0	0,3	0,4	0,3	0,3	0,3	0,5	0,5	0,7	0,9
23	0,2	0,3	0,2	0,2	0,1	0,2	0,3	0,8	0,9	0,3	0,4	0,3	0,3	0,2	0,4	0,5	0,7	1,0	0,4	0,5	0,4	0,4	0,4	0,5	0,5	0,7	0,9
24	0,3	0,3	0,2	0,2	0,1	0,2	0,2	0,7	0,8	0,3	0,4	0,3	0,3	0,2	0,3	0,4	0,7	0,9	0,4	0,5	0,4	0,4	0,3	0,4	0,5	0,6	0,9
25	0,4	0,4	0,3	0,3	0,2	0,2	0,2	0,6	0,7	0,4	0,5	0,4	0,4	0,3	0,3	0,4	0,6	0,9	0,5	0,6	0,5	0,5	0,4	0,4	0,5	0,6	0,8
26	0,7	0,7	0,6	0,6	0,5	0,4	0,2	0,3	0,4	0,7	0,7	0,7	0,6	0,5	0,4	0,2	0,3	0,5	0,8	0,8	0,7	0,6	0,5	0,4	0,3	0,3	0,5
27	0,7	0,7	0,7	0,6	0,5	0,4	0,3	0,3	0,4	0,8	0,8	0,7	0,6	0,5	0,4	0,3	0,3	0,5	0,8	0,8	0,8	0,7	0,5	0,4	0,3	0,3	0,5
28	0,0	0,0	0,1	0,1	0,2	0,3	0,4	0,9	1,0	0,1	0,2	0,1	0,2	0,3	0,5	0,6	0,9	1,1	0,2	0,3	0,2	0,3	0,4	0,5	0,6	0,8	1,0
29	0,0	0,0	0,1	0,1	0,2	0,3	0,4	0,9	1,0	0,1	0,1	0,0	0,1	0,2	0,4	0,6	0,8	1,1	0,2	0,2	0,2	0,2	0,4	0,5	0,6	0,7	1,0
30	0,1	0,1	0,0	0,1	0,1	0,3	0,4	0,8	1,0	0,1	0,2	0,1	0,1	0,2	0,4	0,5	0,8	1,1	0,2	0,3	0,2	0,3	0,3	0,5	0,6	0,7	1,0
31	0,1	0,1	0,1	0,0	0,1	0,2	0,3	0,8	0,9	0,2	0,2	0,1	0,1	0,1	0,3	0,5	0,8	1,0	0,3	0,3	0,2	0,2	0,3	0,4	0,5	0,6	0,9
32	0,2	0,2	0,1	0,1	0,0	0,1	0,3	0,7	0,9	0,3	0,3	0,2	0,2	0,1	0,3	0,4	0,7	1,0	0,3	0,4	0,3	0,3	0,3	0,4	0,5	0,6	0,9
33	0,3	0,3	0,3	0,2	0,1	0,0	0,2	0,6	0,8	0,3	0,4	0,3	0,2	0,1	0,2	0,3	0,6	0,9	0,4	0,4	0,4	0,3	0,2	0,3	0,4	0,5	0,8
34	0,4	0,4	0,4	0,3	0,3	0,2	0,0	0,5	0,6	0,5	0,5	0,4	0,4	0,2	0,2	0,2	0,5	0,7	0,5	0,6	0,5	0,4	0,3	0,3	0,3	0,4	0,7
35	0,9	0,9	0,8	0,8	0,7	0,6	0,5	0,0	0,1	0,9	0,9	0,9	0,8	0,7	0,6	0,4	0,1	0,2	0,9	1,0	0,9	0,8	0,6	0,6	0,4	0,3	0,2
36	1,0	1,0	1,0	0,9	0,9	0,8	0,6	0,1	0,0	1,0	1,0	1,0	0,9	0,8	0,7	0,5	0,2	0,2	1,1	1,1	1,0	0,9	0,8	0,7	0,6	0,4	0,2
37	0,1	0,1	0,1	0,2	0,3	0,3	0,5	0,9	1,0	0,0	0,1	0,1	0,2	0,3	0,5	0,6	0,9	1,1	0,1	0,2	0,1	0,2	0,4	0,5	0,6	0,7	1,0
38	0,2	0,1	0,2	0,2	0,3	0,4	0,5	0,9	1,0	0,1	0,0	0,1	0,2	0,3	0,5	0,6	0,9	1,1	0,0	0,1	0,1	0,2	0,4	0,5	0,6	0,7	1,0
39	0,1	0,0	0,1	0,1	0,2	0,3	0,4	0,9	1,0	0,1	0,1	0,0	0,1	0,2	0,4	0,5	0,8	1,1	0,1	0,2	0,1	0,2	0,3	0,5	0,6	0,7	1,0
40	0,2	0,1	0,1	0,1	0,2	0,2	0,4	0,8	0,9	0,2	0,2	0,1	0,0	0,1	0,3	0,4	0,7	1,0	0,2	0,2	0,2	0,1	0,2	0,4	0,5	0,6	0,9
41	0,3	0,2	0,2	0,1	0,1	0,1	0,2	0,7	0,8	0,3	0,3	0,2	0,1	0,0	0,2	0,4	0,7	0,9	0,3	0,4	0,3	0,2	0,2	0,3	0,4	0,5	0,8
42	0,5	0,4	0,4	0,3	0,3	0,2	0,2	0,6	0,7	0,5	0,5	0,4	0,3	0,2	0,0	0,2	0,5	0,8	0,5	0,5	0,5	0,3	0,1	0,1	0,2	0,3	0,7
43	0,6	0,6	0,5	0,5	0,4	0,3	0,2	0,4	0,5	0,6	0,6	0,5	0,4	0,4	0,2	0,0	0,3	0,6	0,6	0,6	0,6	0,5	0,3	0,2	0,1	0,2	0,5
44	0,9	0,8	0,8	0,8	0,7	0,6	0,5	0,1	0,2	0,9	0,9	0,8	0,7	0,7	0,5	0,3	0,0	0,3	0,9	0,9	0,9	0,7	0,6	0,5	0,3	0,2	0,2
45	1,1	1,1	1,1	1,0	1,0	0,9	0,7	0,2	0,2	1,1	1,1	1,1	1,0	0,9	0,8	0,6	0,3	0,0	1,1	1,2	1,1	1,0	0,9	0,8	0,6	0,5	0,1
46	0,2	0,2	0,2	0,3	0,3	0,4	0,5	0,9	1,1	0,1	0,0	0,1	0,2	0,3	0,5	0,6	0,9	1,1	0,0	0,1	0,0	0,2	0,4	0,5	0,6	0,8	1,1
47	0,3	0,2	0,3	0,3	0,4	0,4	0,6	1,0	1,1	0,2	0,1	0,2	0,2	0,4	0,5	0,6	0,9	1,2	0,1	0,0	0,1	0,2	0,4	0,5	0,6	0,8	1,1
48	0,2	0,2	0,2	0,2	0,3	0,4	0,5	0,9	1,0	0,1	0,1	0,1	0,2	0,3	0,5	0,6	0,9	1,1	0,0	0,1	0,0	0,1	0,3	0,5	0,6	0,7	1,0
49	0,3	0,2	0,3	0,2	0,3	0,3	0,4	0,8	0,9	0,2	0,2	0,2	0,1	0,2	0,3	0,5	0,7	1,0	0,2	0,2	0,1	0,0	0,2	0,4	0,5	0,6	0,9
50	0,4	0,4	0,3	0,3	0,3	0,2	0,3	0,6	0,8	0,4	0,4	0,3	0,2	0,2	0,1	0,3	0,6	0,9	0,4	0,4	0,3	0,2	0,0	0,2	0,3	0,4	0,8
51	0,5	0,5	0,5	0,4	0,4	0,3	0,3	0,6	0,7	0,5	0,5	0,5	0,4	0,3	0,1	0,2	0,5	0,8	0,5	0,5	0,5	0,4	0,2	0,0	0,1	0,3	0,7
52	0,6	0,6	0,6	0,5	0,5	0,4	0,3	0,4	0,6	0,6	0,6	0,6	0,5	0,4	0,2	0,1	0,3	0,6	0,6	0,6	0,6	0,5	0,3	0,1	0,0	0,2	0,5
53	0,8	0,7	0,7	0,6	0,6	0,5	0,4	0,3	0,4	0,7	0,7	0,7	0,6	0,5	0,3	0,2	0,2	0,5	0,8	0,8	0,7	0,6	0,4	0,3	0,2	0,0	0,4
54	1,0	1,0	1,0	0,9	0,9	0,8	0,7	0,2	0,2	1,0	1,0	1,0	0,9	0,8	0,7	0,5	0,2	0,1	1,1	1,1	1,0	0,9	0,8	0,7	0,5	0,4	0,0

Detail of Euclidean Distances between the cells.

Table 1: Stock Markets' Sample

Amman SE	Hong Kong Exchanges	NASDAQ OMX Nordic Copenhagen
Athens Exchange	Indonesia SE	National Stock Exchange India
Australian SE	Irish SE	New Zealand Exchange
Bermuda SE	Japan Exchange Group - Osaka	NYSE Euronext (US)
BM&FBOVESPA	Japan Exchange Group - Tokyo	Oslo Bors
BME Spanish Exchanges	Johannesburg SE	Philippine SE
Borsa Istanbul	Korea Exchange	Santiago SE
Borsa Italiana	Lima SE	Shanghai SE
BSE India	Ljubljana SE	Shenzhen SE
Budapest SE	London SE	Taiwan SE Corp.
Buenos Aires SE	Luxembourg SE	Tehran SE
Bursa Malaysia	Malta SE	Tel Aviv SE
Colombia SE	Mauritius SE	The Stock Exchange of Thailand
Colombo SE	Mexican Exchange	TMX Group
Cyprus SE	MICEX	Warsaw SE
Deutsche Borse	NASDAQ OMX	Wiener Borse
Egyptian Exchange		

Table 2: Statistics of the Blue Group (B), the Green Group (G) and the Red Group (R)

Group B	Domestic Market Capitalization (DMC)	Electronic Turnover Domestic (ETD)	Electronic Turnover Foreign (ETF)	Listing Domestic (LD)	Listing Foreign (LF)	Market Cap New Listings (MCNL)	Trading Days (TD)	Euclidean Distance
Average	195,724	127,437	6,920	275	19	5,142	246	0.16
STD	276,319	261,673	20,648	238	46	7,907	8	0.12
5% Percent	4,248	208	0	23	0	33	231	0.00
95% Percent	801,593	752,278	48,113	876	50	25,399	253	0.41
Min	1,505	49	0	14	0	0	202	0.00
Max	1,411,759	1,384,426	124,235	994	253	37,174	257	0.41
Group G								
Average	974,494	941,564	15,210	1,900	28	49,201	251	0.40
STD	491,420	588,698	26,571	1,451	34	81,908	7	0.15
5% Percent	285,501	202,661	0	634	0	3,867	236	0.21
95% Percent	1,716,895	1,884,085	62,203	4,943	89	116,753	259	0.60
Min	252,893	73,327	0	582	0	2,233	231	0.21
Max	2,287,042	2,601,515	115,223	5,764	121	454,409	261	0.60
Group R								
Average	5,177,132	7,306,168	549,721	2,258	308	117,384	248	0.90
STD	4,040,461	5,558,680	634,074	596	207	45,572	8	0.20
5% Percent	2,087,888	1,621,538	248	1,415	8	49,851	236	0.66
95% Percent	12,947,696	17,608,669	1,711,716	3,108	548	181,766	254	1.10
Min	1,868,153	1,146,641	0	903	0	42,791	225	0.66
Max	14,272,543	18,431,736	1,827,475	3,535	629	195,069	255	0.66

Note: data for DMC, ETD, ETF and MCNL are in millions USD.

Table 3: Total amount for each variable during each of the three periods considered

	Group B			Group G			Group R		
	2000/03	2004/07	2008/12	2000/03	2004/07	2008/12	2000/03	2004/07	2008/12
Domestic Market Capitalization (DMC)	3,992,295	6,106,160	7,516,679	2,872,903	12,702,409	12,685,000	18,377,204	25,670,805	23,254,712
Electronic Turnover Domestic (ETD)	3,092,616	3,069,440	5,307,267	2,601,560	12,104,696	12,599,112	18,566,427	35,421,500	40,992,251
Electronic Turnover Foreign (ETF)	190,144	198,434	234,185	11,652	183,526	245,912	1,118,400	2,669,752	3,358,223
Listing Domestic (LD)	8,494	6,754	9,541	12,835	20,918	21,356	9,971	9,688	9,691
Listing Foreign (LF)	647	449	598	127	323	365	1,347	1,235	1,429
Market Cap New Listings (MCNL)	166,962	146,546	149,229	141,706	851,136	433,998	546,154	469,144	510,692

Note: data for DMC, ETD, ETF and MCNL are in millions USD.

Table 4: Changes in variables according to Euclidean distance.

	Group B		Group G		Group R	
	2004/07 w.r. 2000/03	2008/12 w.r. 2004/07	2004/07 w.r. 2000/03	2008/12 w.r. 2004/07	2004/07 w.r. 2000/03	2008/12 w.r. 2004/07
Domestic Market Capitalization (DMC)	53%	23%	342%	0%	40%	-9%
Electronic Turnover Domestic (ETD)	-1%	73%	365%	4%	91%	16%
Electronic Turnover Foreign (ETF)	4%	18%	1475%	34%	139%	26%
Listing Domestic (LD)	-20%	41%	63%	2%	-3%	0%
Listing Foreign (LF)	-31%	33%	154%	13%	-8%	16%
Market Cap New Listings (MCNL)	-12%	2%	501%	-49%	-14%	9%

Figure 1. Each cell in the input layer includes six connections, one for each cell in the output layer. Each cell in the output layer has three entry points, one for each cell in the input layer.

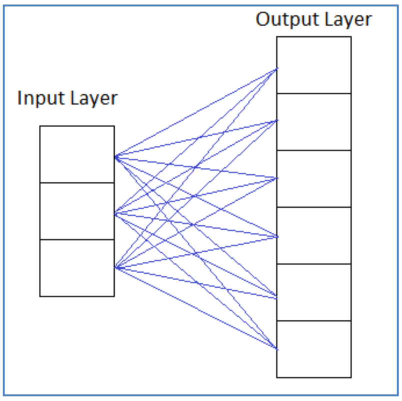
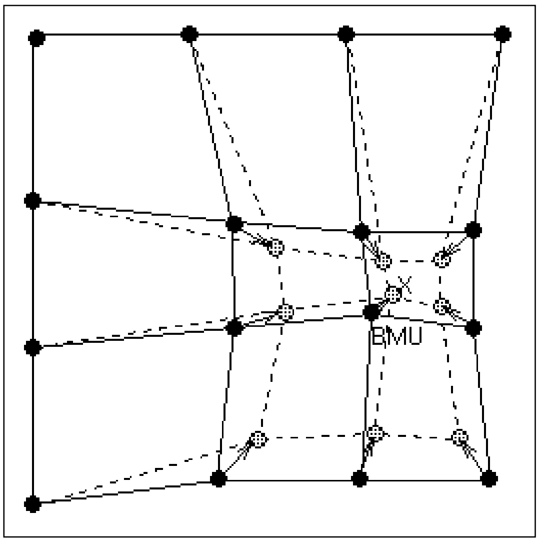


Figure 2: Updating of the winning neuron (BMU) and its neighbors, moving them towards the input vector, marked by an X.



Source: (Kohonen T. , Self-Organized formation of topologically correct feature maps, 1982)

Figure 3: Unified Matrix of the model.

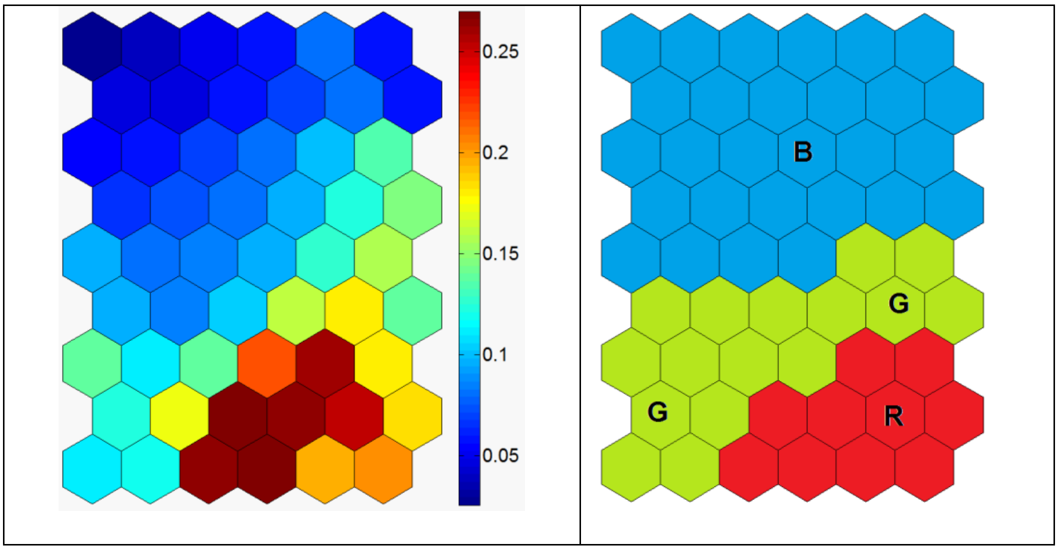


Figure 4: Classification according to the different variables

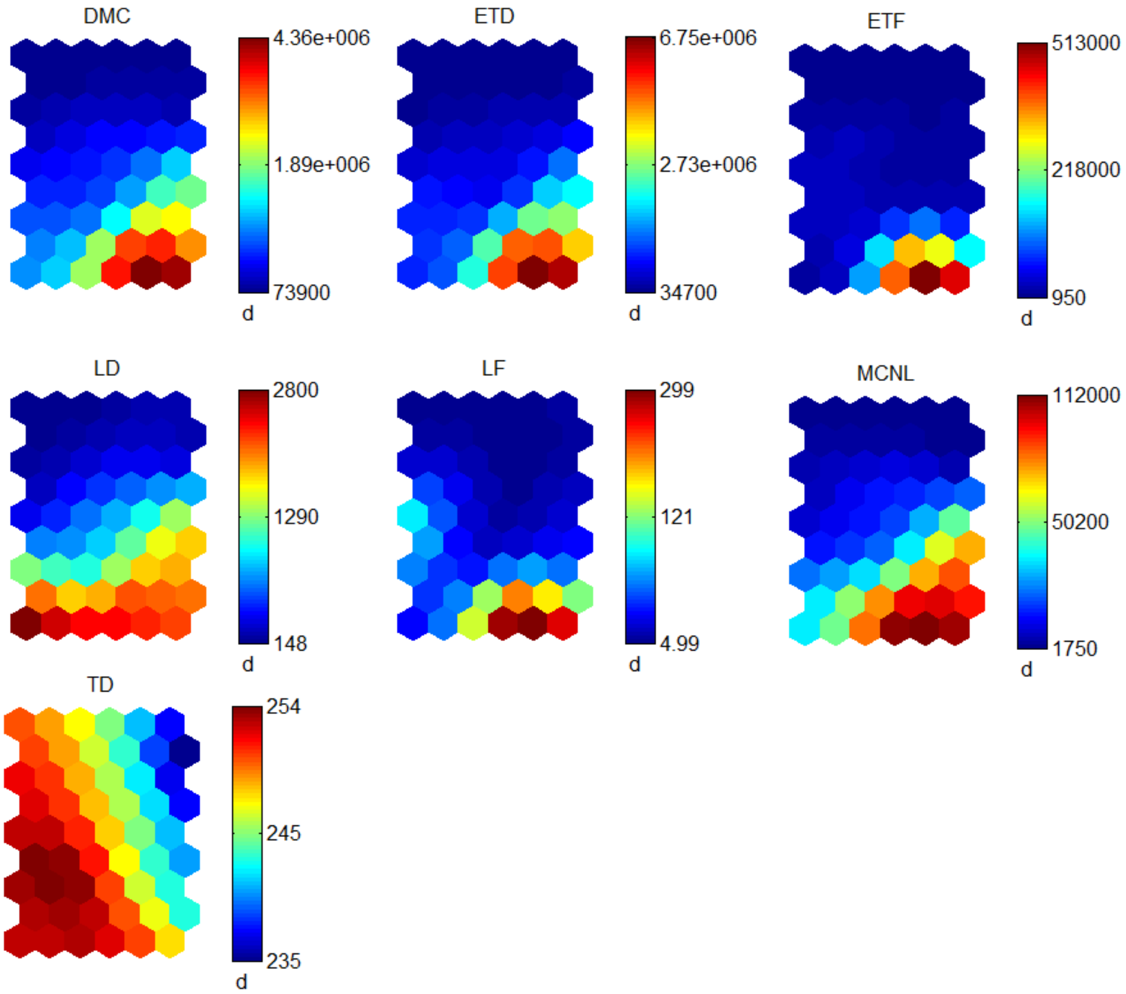


Figure 5: Stock Market Mapping and Evolution From 2000 to 2012:

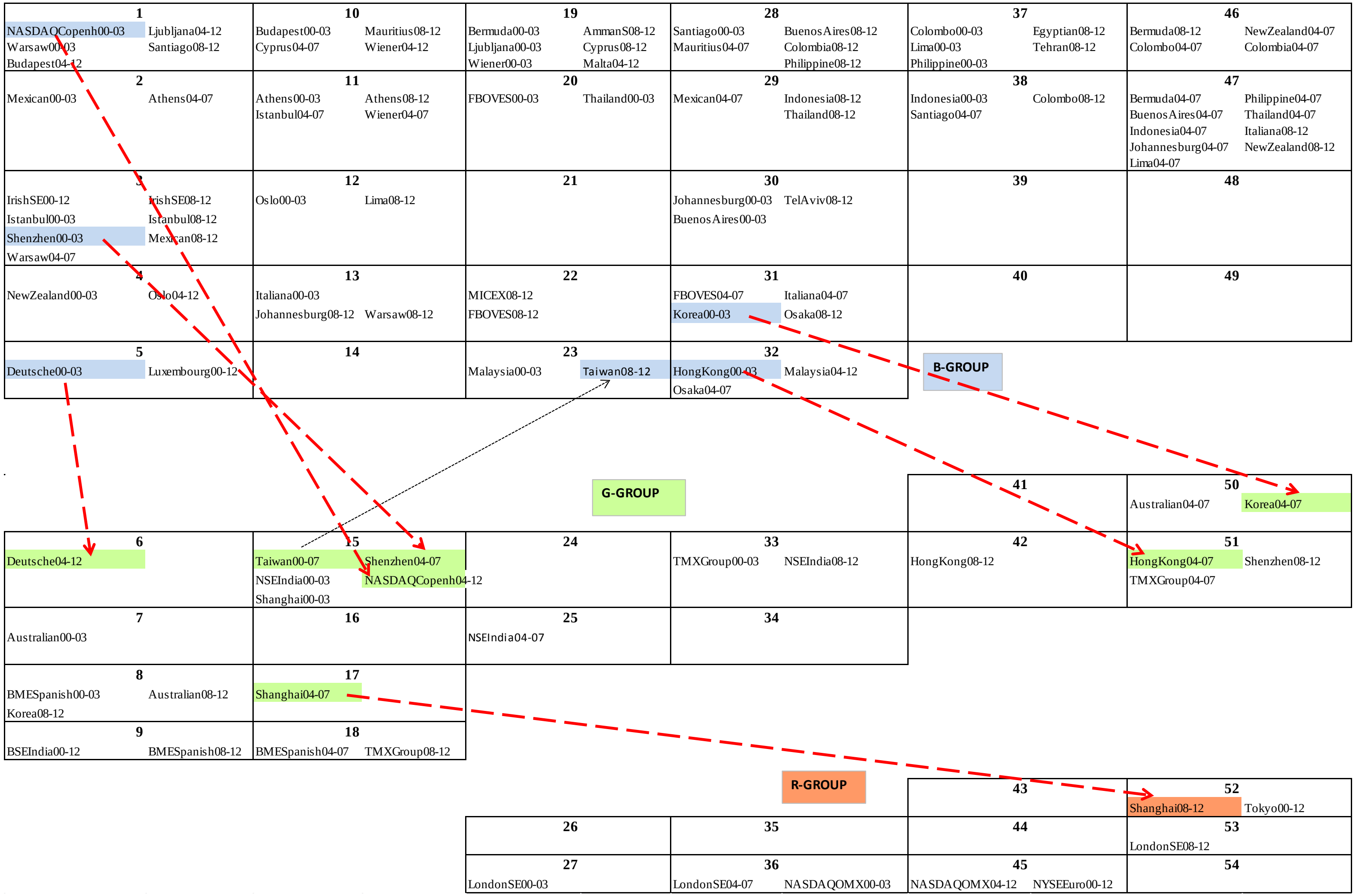


Figure 6: Euclidean Distances with values below 0.2

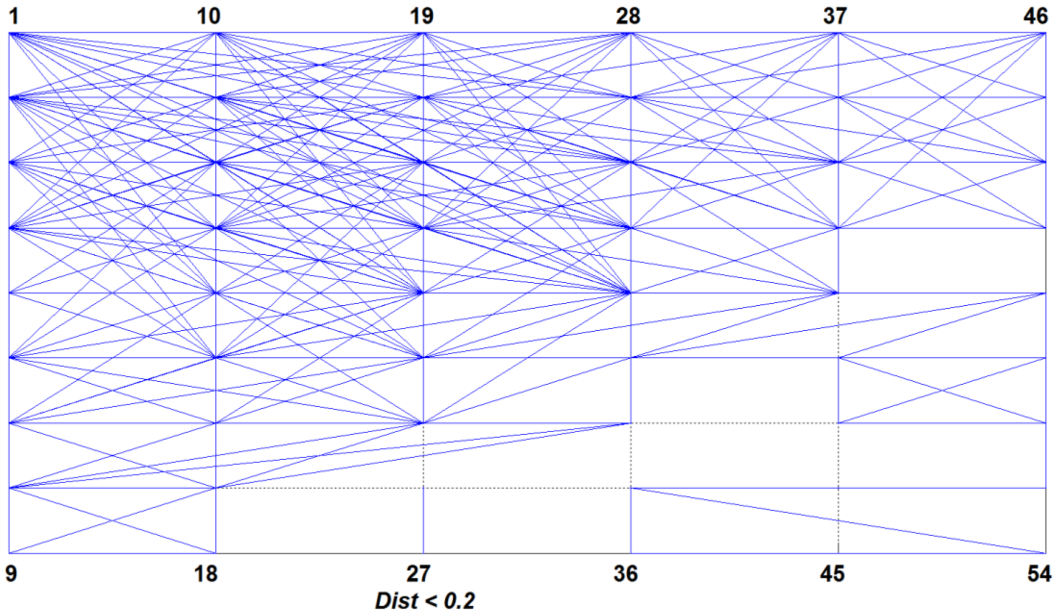


Figure 7: 3-D Distribution of the markets