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The integration of the European financial sector – the case of the banking sector

Abstract

In this study we use the self-organizing map (SOM) algorithm for constructing the topology of Europe's banking sector. The SOM algorithm can be used to visualize the most central property of high dimensional data, namely its cluster structure on a projected graphical map display that is easily understandable. In addition to the selected method, the use of large database separates this study from those carried out in the past. The database includes data for 27 countries and 2 integrations (EU and EMU). The data cover the period from 1997 to 2007 and each country is characterized by 17 variables. This gave us the opportunity to study the trajectory movement of the banking sectors over the years and trace the dominating cause of such movements over time. Our main result is that the banking systems of European countries have gone through remarkable institutional development and integration. However, the integration project is far from over. Real integration has proceeded quite far in response to the liberalization of trade, but financial integration remains incomplete. If we examine properties of individual variables, we can see that only two variables directly support the division of countries in the two major groups (east-west or right-left side of the map). Other variables show more complex structures in the map and therefore support the idea of nonlinearities. The weights for many variables indicate outliers, which we also expected in the setup of our study.

Keywords: financial sector, banking system, cluster analysis, neural networks, integration process.
JEL Classification: G21, F36, C45.

Introduction

The goal of this research is to examine whether banking sector integration exists among EU countries. Many studies have demonstrated that financial markets of EU exhibit high degree of integration. In contrast to expectations, the banking sector is usually found to be the least homogeneous segment of the European financial system (Baele et al., 2004; Cabral et al., 2002 and Corvoisier and Gropp, 2001).

Various methods allow a quantitative assessment of the degree of financial integration and are based on: (i) interest rate data; (ii) bank structure data (branches versus subsidiaries); (iii) mergers and acquisitions data; and (iv) bank concentration data (see, for example, Galati and Tsatsamoris, 2001; Fratzscher, 2001; Giannetti et al., 2002; Kleimeier and Sander, 2002; Adam et al., 2002; Hartmann et al., 2003; Adjouté and Danthine, 2003; and Manna, 2004). In this study, we have deviated from the standard methods of analyzing financial integration. We instead try to apply a cluster analysis, with the objective to detect some patterns in the European financial system when it comes to the degree of homogeneity among countries.

Cluster analysis is a useful tool for examining complex relationships among national characteristics and international linkages without imposing any *a priori* restrictions on these interrelationships. This feature makes cluster analysis an attractive tool for analyzing a large amount of complex data, and can therefore be employed in the analysis of the banking sector (Sørensen and Puigvert Gutiérrez, 2006). Due to the numerical simplicity, mostly standard linear techniques have been selected, which suffer from many drawbacks, such as the assumption of linearly separable clusters. Therefore, we have decided to employ the Self-Organizing Map (SOM), which belongs to the class of techniques that are generally known as artificial intelligence techniques. We believe that SOM may provide a better classification of banking sectors in terms of their structural characteristics and also help us identify the defining features of various clusters among countries, classified according to their characteristics.

What separates this study from those carried out in the past is not only the selected method, but also the significantly large database. The database included data for 27 countries and 2 integrations (EU and EMU). The data cover the period from 1997 to 2007 and each country is characterized by 17 variables. This gave us the opportunity to study the trajectory movement of the banking sectors over the years and trace the dominating cause of such movements over time, with the help of component plane visualizations in the SOM.

The rest of the paper is organized as follows: In section 1, we will discuss the artificial intelligence SOM methodology. The data are presented in Section 2. Section 3 presents the empirical study using the SOM technique. Finally, in the final section, we will note our conclusions and significant observations.

1. Self-organizing maps as method for detecting clusters

The objective of cluster analysis is to search inside data for groups of countries in which countries belonging to the same group would have their attributes closer to each other, but that at the same time would differ from countries belonging to other groups. Cluster analysis imposes no *a priori* restrictions on the structure of the data and requires no assumptions about the probabilistic nature of the observations. However, the application of cluster analysis does have some limitations. For example, it may be difficult to determine the correct number of clusters, or whether the clusters formed from the data are statistically significant or just a result of randomly occurring concentrations of observations within an original distribution (Korobow and Stuhr, 1991). Hence, although cluster analysis is very useful for describing data, it should be characterized as a statistical exploratory technique (Hair et al., 1998).

When applying cluster analysis, it is important to select the appropriate type of clustering technique. The most commonly used technique has been the statistical technique of Principal Component Analysis (PCA), which is essentially a dimension reduction technique. Although standard statistical dimension reduction techniques carry the advantage of simplicity, they suffer from some important limitations, foremost their poor data visualization capabilities and their inability to appropriately account for possible nonlinear relationships among the indicators. In fact, from a policy perspective, it is not important to merely rank the individual country against a constructed scalar measure, as the distance on the synthetic scale of a scalar measure may not have much informational value. What is more important is knowing what countries exhibit a similarity in terms of various indicators and the defining characteristics of these well-formed clusters. The transition of an individual country from one cluster to another over time is also an important indicator of reform measures.

We believe that the Self-Organizing Map (SOM) may provide a better classification of the banking sectors in terms of their overall performance and help us identify the defining features of the various cluster of countries classified according to their characteristics. The SOM algorithm can be used for visualizing the most central property of high dimensional data, namely its cluster structure on a projected graphical map display that is easily understandable. The SOM algorithm is thus a unique method that serves the twin goal of the projection and clustering techniques.

SOM is a feed forward neural network that uses an unsupervised training algorithm, and through a process called selforganization, configures the output units into a topological representation of the original data (Kohonen, 2001). SOM belongs to a general class of neural network methods, which are non-linear regression techniques that can be trained to learn or find relationships between inputs and outputs or to organize data so as to disclose hitherto unknown patterns or structures.

Supervised neural network techniques demand that one or more outputs are specified in conjunction with one or more inputs to find patterns or relations between data. In contrast, SOM reduces multidimensional data to a visualizable lower dimensional map or grid of neurons. The aim of Kohonen's self-organizing map is thereby to capture the topology of the multidimensional input data, providing a topology-preserving mapping from the high dimensional space to the map units.

The network maps a set of input vectors $x_k \in \Re$ onto a two-dimensional lattice grid (it is also possible to project the vector on a one or three dimensional grid). Similar or related patterns in the input space are mapped to nearby grid units, thus preserving the topological relationships among patterns. The input vectors are organized on the lattice grid through competitive learning. The process of creating an SOM requires two layers of processing units; the first is the input layer containing each element of the input vector, the second is an output layer or grid of processing units that are fully connected with those at the input layer. The number of processing units at the output layer is decided by the user, which is based on the initial shape and size of the map that is desired.

Unlike other neural network structures, SOM structure does not have any hidden layer of neurons. Each unit in the SOM output lattice grid is uniquely characterized by an n-dimensional model vector $m_i (m_i \in \Re^n)$. The components of m_i correspond to synaptic weights. When an input vector x_k (chosen at random) is presented to the network, the distances between x_k and all the m_i are calculated. The most typical and well-known distances that might be used are the Euclidean and squared Euclidean distance, the Manhattan or city block distance, the Mahalanobis distance or the Chebychev distance, among others. The final choice among them depends on the data and the type of variables collected. The standardization methodology, which we applied to the data, is not appropriate for the Mahalanobis distance, since it would mean standardizing again through the classical method of standardization. Moreover, the variables finally used are relatively weakly correlated which is a good reason to use the Euclidean or squared Euclidean distance (Everitt, 1993). Furthermore, Euclidean measurements place greater emphasis on outliers to generate distance patterns. Therefore, we decided to use the Euclidean measurement, since we presume that the grouping of countries should be based on a great deal of similarity across all variables and that distinctions should be formed on the basis of outliers (Wolfson et al., 2004).

Such a technique has several advantages over the traditional statistical exploratory data analysis techniques like the Principal Component Analysis (PCA) based projection method or the Statistical Cluster Analysis (SCA) method. A statistical projection-based method, like the PCA, provides a 2-dimensional (or at most 3-dimensional) projection of multidimensional data. Although such a projection gives some idea about the location of a point on the multidimensional plane, not much can be inferred from the clustering tendencies, the mutual distance between adjacent points on the projected plane, the compactness of clusters, their characterization, cluster boundaries, or the existence of regions with points having a high mutual distance. Furthermore, PCA-based projection provides for a poor projection in cases when the proportion of variance explained through the projected components is not high enough. The SOM projection does not have the aforementioned shortcomings of the PCA-based projection technique. The application of SOM does not require *a priori* knowledge about the number of clusters, which is otherwise required for a k-means clustering technique. In SCA, the total cases are distributed into an exhaustive set of clusters. In this way, a case has to fall into one of the formed clusters. On the other hand, SOM exhibits not only clusters of multidimensional data, but also cases that do not form any cluster, and isolated cases. SOM is technically better equipped to handle outliers than traditional cluster analysis techniques. The mutual distance between points in the multidimensional plane is visualized by means of a two-dimensional distance on the SOM plane. SCA-based clustering methods are not equipped to demonstrate such visualization and analysis of data. Inspection of SOM along with its component plane visualization facilitates quick understanding of the multidimensional data, their clustering patterns, depth of clusters and characterization. Traditional SCA-based methods do not allow for the visualization of multidimensional data that facilitates easy understanding and interpretation.

2. Selection of countries and variables

In section two, we presented the possible methods for performing cluster analysis and explained why we selected SOM. This type of method belongs to nonlinear clustering methods and therefore requires a large number of observations in a sample in order to achieve stable results. In this study, the number of observations can be increased in two ways: by increasing the number of analyzed countries and by creating pooled data (gathering data from different time periods for the selected countries). Both strategies have been selected and the final version of the database is presented in Table 1. The data were collected for 27 European countries on an annual basis for the period from 1997 to 2007.

By using cluster analysis on different time periods, it is possible to analyze how different countries evolve over time. Our objective is to precisely detect whether all countries remain stable over time or whether they evolve with a particular trend or characteristic. As previously noted, we expect some groups of countries to remain stable, but also a reduction in the distance between the different groups would be expected, because it would imply that over time more countries have the same characteristics. This could be interpreted as a gradually more homogeneous and integrated banking sector among European countries.

Cluster analysis implies that no restrictions or predetermined structures are imposed upon the data *ex ante*. The selection of variables to be included in the cluster analysis is therefore highly important, since it is the data itself that structures the results. Leaving out or adding an important variable can therefore alter the results significantly. The variables we used were selected with the aim to capture as much as possible the behavior and structure of the banking sector in European countries – taking into account studies of the banking sector (e.g., Wong, 1997; Saunders and Schumacher, 2000; and Maudos and de Guevera, 2004).

Table 1. Sample selection

Country	Code	Time covered	Sub-sample size	Country	Code	Time covered	Sub-sample size
Austria	AT	1997-2007	11	Italy	IT	1997-2007	11
Belgium	BE	1997-2007	11	Lithuania	LT	2002-2007	6
Bulgaria	BG	2003-2007	5	Luxembourg	LU	1997-2007	11
Cyprus	CY	2002-2007	6	Latvia	LV	2001-2007	7
Czech Republic	CZ	2002-2007	6	Malta	MT	2001-2007	7
Germany	DE	1997-2007	11	European Monetary Union	MU	1999-2007	9
Denmark	DK	2002-2007	6	Netherlands	NL	1997-2007	11
Estonia	EE	2001-2007	7	Poland	PL	2001-2007	7
Spain	ES	1997-2007	11	Portugal	PT	1997-2007	11
European Union	EU	2001-2007	7	Romania	RO	2003-2007	5
Finland	FI	1997-2007	11	Sweden	SE	2000-2007	8
France	FR	1997-2007	11	Slovenia	SI	2001-2007	7
Greece	GR	2000-2007	8	Slovakia	SK	2002-2007	6
Hungary	HU	2001-2007	7	United Kingdom	UK	1997-2007	11
Ireland	IE	1997-2007	11				
Total sample size: 246							

Since we selected a large number of countries, it was difficult to gather many variables, which could be important in explaining the nature of the banking sector across countries. We also noticed that data for the same variables from different sources vary considerably. To avoid the problem of inconsistency in data due to different sources, we used only data provided by the ECB and EUROSTAT. This resulted in a list of selected variables, which is presented in Table 2 together with the basic statistical properties of each of the seventeen selected variables.

An important segment that was not included: the factors affecting the supply of and demand for credit/deposits – a type of cyclical indicator. However, such indicators might have a substantial impact on the results and hence the observed clustering may to some extent reflect cyclical variations/similarities rather than structural developments in the banking sector.

For some countries, there are missing variables with respect to some of the series, which forced us to work with an unbalanced panel. Additionally, data for the averages of the European Union and European Monetary Union have been added. Each variable has been standardized using its own maximum and minimum value over all periods. Without standardization, the variables with a larger scale would have a greater impact on each cluster than other variables and would hence dominate and potentially bias the results. This type of transformation is a more robust measure than the normal standardization method because its denominator is more sensitive to observations far away from the center.

Table 2. List of selected variables

Variable		Min.	Max	Mean	Std.	Kurt.	Skew.	JB
1	Number of credit institutions	8,37E-06	0,57	0,05	0,11	11,18	3,46	1177,43
2	Number of local units (branches)	2,31E-04	1,40	0,42	0,26	2,01	1,19	68,53
3	Number of employees of CIs	4,73E-05	0,54	0,08	0,10	15,07	3,92	2121,29
4	Total assets of CIs	2,85E-02	3,35	0,35	0,56	16,93	4,17	2702,48
5	Herfindahl Index for CIs	1,14E-02	0,41	0,10	0,08	3,99	1,76	137,38
6	Share of the 5 largest CIs in total assets (in percent)	1,70E-01	0,99	0,55	0,20	-0,76	0,14	145,94
7	Loans of CIs to non-financial corporations	7,36E-03	0,20	0,04	0,03	8,82	2,72	650,28
8	Total loans of CIs for housing purchase	4,83E-04	0,10	0,03	0,02	1,04	0,94	75,29
9	Total loans of CIs for consumer credit	3,26E-04	0,02	0,01	0,00	2,22	1,14	59,40
10	Other household lending from CIs	9,50E-05	0,06	0,01	0,01	8,57	2,93	669,39
11	Total loans of CIs to non-CIs	1,47E-02	0,66	0,13	0,11	9,55	2,85	773,03
12	Total deposits of CIs from non-CIs	1,82E-02	1,34	0,13	0,19	18,42	4,21	3161,58
13	Number of branches of CIs from EU countries	0,00E+00	0,14	0,01	0,02	23,19	4,86	5146,53
14	Number of branches of CIs from third countries	0,00E+00	0,03	0,00	0,01	11,02	3,47	1152,18
15	Number of subsidiaries of CIs from EU countries	2,56E-07	0,23	0,01	0,04	19,45	4,54	3617,84
16	Number of subsidiaries of CIs from third countries	0,00E+00	0,11	0,00	0,02	19,66	4,57	3699,12
17	Total assets of subsidiaries of CIs from EU countries	3,88E-04	2,25	0,13	0,41	17,99	4,41	3101,83

Notes: N = 246 for all variables. * JB test statistic is significant at p = 0,001 for all variables.

3. Analysis of the results

When the input space is high dimensional, the interpretation of results is a challenging task. The application of SOM helps us detect structures in such a high dimensional space. Based on the results, we prepared a picture of the topology of the banking sector in European countries (see Figure 1). Since we also observed changes in the topology over time, we have indicated the time dimension with arrows, where the beginning of the arrow represents the first observation for a selected country and the ending the last observation. As already presented in section two, the last observations for all countries are from the year 2007.

When looking at the results in Figure 1, some patterns can be observed. Generally, we can divide the topology of the banking sector into two parts – east and west (the left and right part of the map).

If we first observe the left part of the map, one central cluster appears. This cluster consists of Germany, Italy, Austria, and France. It is also interesting that they jointly move towards the center of the map – they drift from left to center. This drift can also be observed for the average data of the EU. Additionally, the average properties of the EMU have the same tendency and most of the time, the EMU (as an average) is in the cluster of these four countries. The only exception was the year 1999, during which the EMU was not present in this cluster.

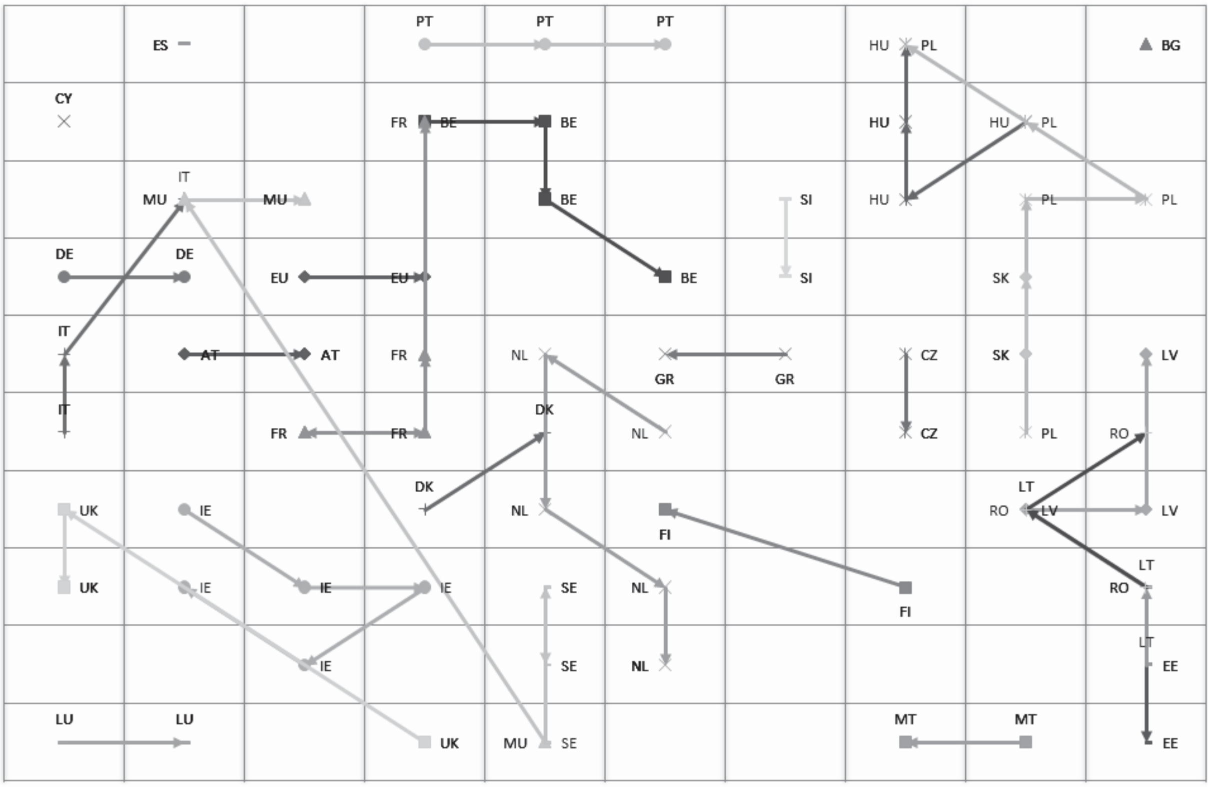

Fig. 1. Evolving topology of the banking sector in EU

The cluster of Germany, Italy, Austria and France neighbors three other clusters. On the top-left side is the cluster formed by Cyprus, Spain and Portugal. This cluster has an interesting dynamic, since Cyprus and Spain remain at the same position throughout the observed period. In the beginning, Portugal was close to Spain, which may partly reflect the geographical and cultural proximity of the two countries and the fact that they follow a broadly similar economic and financial development, including some cross-border mergers, since joining the EU in 1986. But the results suggest that Portugal is drifting away from Spain and in the same direction as the countries in the first cluster. Therefore, we can conclude that Portugal is probably importantly changing the characteristics of its banking sector so that the similarities with Spain are no longer present.

The next cluster, which borders the central cluster of Germany, Italy, Austria, and France, is at the bottom-left side of the map. The cluster is formed by the United Kingdom, Ireland and Luxembourg. An interesting property of this cluster is that the banking sector in Ireland seemed to follow the path of development in the United Kingdom. Both countries moved closer to the central cluster, but still remain close to Luxembourg, which is located at the bottom-left corner of the map. This position, like in the case of Spain and Cyprus, indicated banking sector properties that strongly deviate from other countries.

The United Kingdom, Ireland and Luxembourg differ from other countries by many indicators. This is also reflected by the fact that they represent traditional financial hubs. They are also characterized by "inward Europeanization", since the total assets held by EU banks in these countries are notably higher than the total assets held by banks from these countries in the EU.

Denmark, the Netherlands, Sweden, and Finland are countries that were, in the beginning of the observed period, located far apart from each other. However, they moved closer to each other by the end of the observed period and formed a cluster, which is positioned at the right side of the central cluster. The grouping of Finland, Sweden, Netherlands, and Denmark may indicate an Anglo-Saxon type of financial system. These countries also show similarities in terms of holding a large amount of assets abroad, indicating "outward Europeanization".

Belgium and Greece are both in a cluster of their own. Greece borders the clusters on the right side of the map and is moving towards the center. The movement towards the central cluster is probably a result of integration into the EMU. The final position in the year 2007 is close to the final position of Belgium.

On the right side of the map are all of the Eastern European countries. This is also not surprising, since the countries are undergoing significant changes in their financial systems. Many of them were marked at the beginning of the observed period by a large number of very small institutions with assets below €0.5 billion. Only in the Czech Republic, Hungary, and Poland there were a few larger institutions. Most of the Eastern European countries also show the common characteristic of a strong rise of banking assets. At the same time, non-bank assets are also growing rapidly. Banks appear to be capable of harnessing this trend towards disintermediation by developing their fee-earning activities, including investment banking and asset management businesses. From a financial stability perspective, this process may be beneficial, because greater diversification and complementary income sources may contribute to lower aggregate risks and to more stable profits, provided that the various income sub-components are not perfectly correlated. On the other hand, channeling risks away from banks to other financial intermediaries (often less regulated) might make risks more opaque.

Most of the new member countries can be grouped into two clusters. The first cluster consists of Hungary, Poland and Slovakia. This cluster emerged at the end of the observed period, because Poland and Slovakia moved closer to Hungary. These countries and the Czech Republic, which is near them, attracted a large number of foreign banks. This probably makes them very similar. The cluster is located in the upper right part of the map, but does not include the corner of the map, where Bulgaria is located. Bulgaria remained in the upper right corner of the map during the entire period under study.

The second group consists of Lithuania, Latvia and Romania. This cluster is located below the first cluster. As in the case of Hungary, Poland, and Slovakia, this cluster is becoming more homogeneous through time. All countries showed a tendency to move up the map – that is, in the direction of the first cluster.

In the bottom-right corner of the map is Estonia. Estonia was first close to Lithuania, which then moved up towards Latvia and Romania. In contrast to other countries on the right side of the map, Estonia moved downwards to a final position at the bottom-right corner, where it was also located. Malta then drifted away.

The closest to the EU and EMU is Slovenia, followed by the Czech Republic. They both form the cluster of their own. The position of Slovenia is probably a result of joining the EMU and the low level of the assets held by foreign banks. It is also worth noting that at the beginning of the period under study, the Czech Republic and Slovakia were close to each other, but by the end, Slovakia joined the cluster formed by Hungary and Poland.

In addition to Figure 1, we also analyzed the weight structure of the SOM. We can visualize the weights themselves using the weight plane figure (see Figure 2). There is a weight plane for each element of the input vector (seventeen in this case, since we use seventeen variables). They are visualizations of the weights that connect each input to each of the neurons. Darker shades represent smaller weights. If the connection patterns of two inputs are very similar, you can assume that the inputs were highly correlated.

If we examine Figure 2, we can see that only two variables directly support the division of countries in the two major groups (east-west or right-left side of the map). These two variables are the Herfindahl Index (variable five) and the share of the five largest credit institutions in total assets (variable six). Variable two (number of local units) divides the map into an upper and lower part. Other variables show more complex structures in the map and therefore support the idea of nonlinearities. The weights for many variables (especially from eleven to seventeen) indicate outliers, which we also expected in the setup of our study.

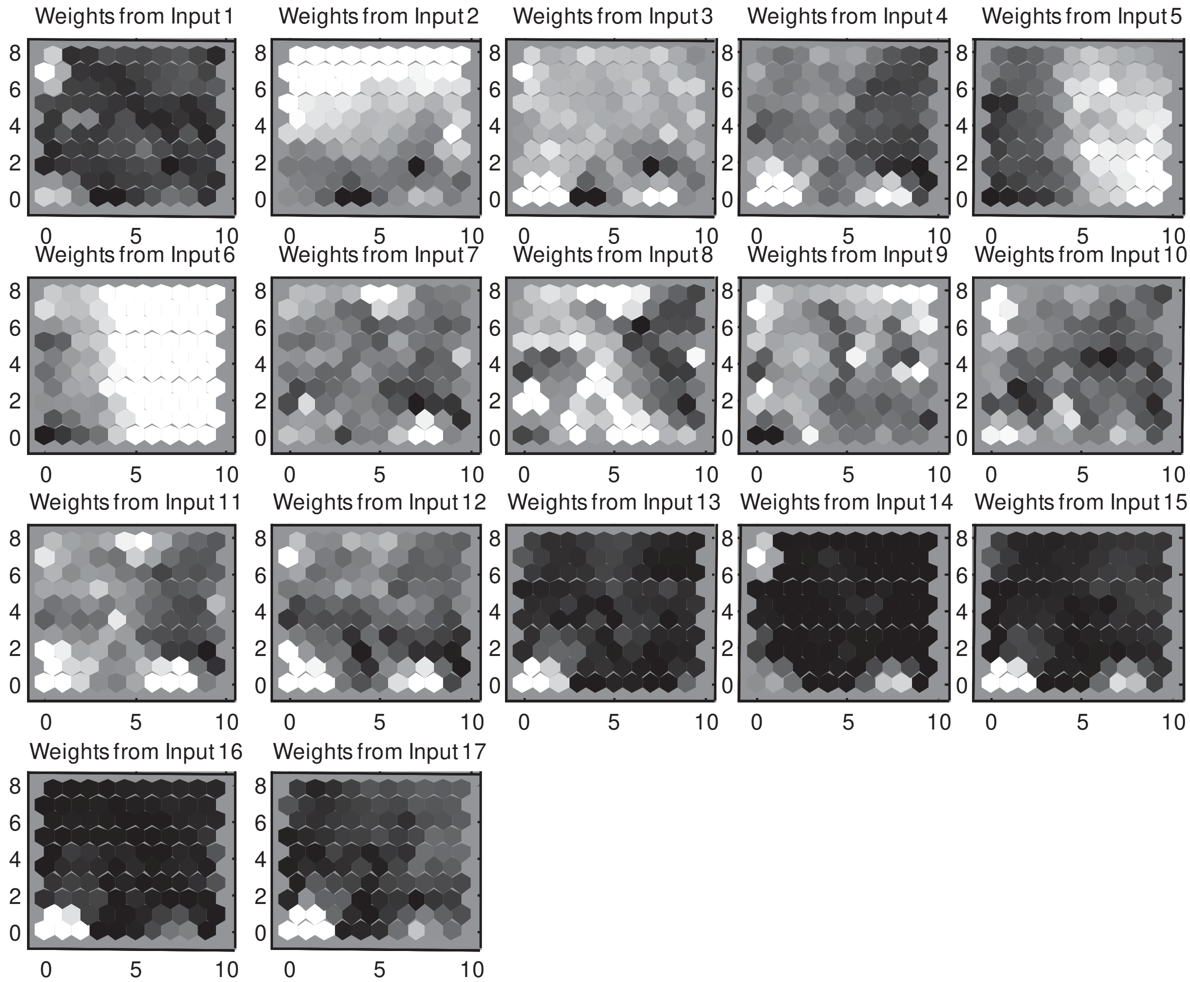

Fig. 2. Weight planes

Conclusion

In this research we examine whether banking sector integration exists among EU countries. Our main result is that the European countries have become more homogeneous during the observed period, although the results indicate considerable differences. The map of the banking sector can be divided into an eastern and western (right and left) part. Additionally, each part of the map can be further divided into logical clusters of countries. Time also plays an important role, since clusters seem to move through the map closer to each other.

The non-homogeneous structure of the European banking sector can be explained by many factors. First, retail lending products are less exposed to international competition pressures as physical distance between banks and customers is quite important. In addition, the presence of asymmetric information and country-specific bank behavior in order to cope with it, as well as transaction costs, cannot be neglected since they also lead to segmentation of both deposit and lending markets.

On the other side, the potential for market integration between EU countries exists due to major role of banks from western European countries in new EU countries´ banking industries regarding their significant ownership stakes, increasing level of euroization and process of joining EMU. High ownership stake of western EU banks offers not only potential for possible integration, but also presents an obstacle for implementation of monetary policy measures in new EU economies, since foreign owned banks in new EU countries respond to the monetary policy impulses coming from ECB and not from their national central banks. As well, these banks are more prone to lending with currency clause or in euro currency as a way to remove increasing exchange rate mismatch from their balance sheets thus creating unofficial financial system euroization as another monetary policy impediment.

Finally, it is important to note that unlike the case of western EU countries where the process of banking industry consolidation took place mainly through mergers and acquisitions within national borders which impeded EU wide banking integration, in new EU countries banking consolidation was conducted through entrance of foreign banks into national banking industries which could have facilitated integration in both deposit and credit markets with old EU countries.

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