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7. The cluster analysis of the banking sector in Europe

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The Cluster analysis aims to conduct an exploratory study on the European banking sector by gathering ranges of consolidated banking indicators from the European Central Bank. The study will determine the similar pattern according to banking sector ratios and changes in the cluster groups affected by the financial crisis. It aims to explore whether the foreign ownership of the banks contribute to the characteristic or clustering of these banks or it is a country specific composition. Our findings confirm that the grouping of the banking sectors based on the banking ratios show that the EU countries in similar geographic area and with higher economic partnership tend to group in the similar cluster.

Keywords: banking fragmentation; euro area; crisis; cluster analysis

1. Introduction

Cyclical financial crises have revealed the danger of systemic risk due to contagion effects given the interconnectedness of modern banking systems. Systemically it is essential identify the key and important banks, as it is one of the key objectives of systemic risk assessment and a necessary precondition for the formulation of macro prudential policy. González-Hermosillo (2008) relates the degree of vulnerability of individual financial institutions with the degree of stress in global market conditions. Their studies presented that if investors' risk appetite is low or global liquidity is tight, small shocks can have large effects on global financial markets and vice versa. The aim of Macro-prudential policy is to provide safeguard and the overall stability of the financial system, this proven that there are potential loops holes in the banking system in the wake of the recent financial crisis. Regulators have learnt the hard way that dependence of the banking sector undermines the benefits of diversification and may lead to a 'fragile' system (Brunnermeier et al. 2009). This has proven to be a major issue in the wake of the recent financial crisis. The debate on macro-prudential policies and potential warning signals of the crisis have been explored by many researchers and regulatory bodies, many of the models constructed before the crisis have proven to be ineffective and many have raised questions whether the contagious are the matter of clustering of banking system.

This study aim to fill the gap by exploring the hierarchical clustering structure of the 26 EU areas by conducting an exploratory analysis based on the consolidated banking indicators from the European Central Bank. The observation is conducted from 2008 to 2013, the country with uncommon cluster will be identified and micro level of analysis will be carried out to explore the justification to why they are in such cluster.

First, the literature review has been made in order to present previous ideas about the use cluster analysis in the banking sector. The study briefly reviews the literature using cluster analysis in the EU. Then we describe our data and methodology using hierarchical clustering analysis technique. Our model provide unique set of grouped categories or clusters by sequentially pairing variables from the selected data. Next section discusses the main results and presents the clustering of the financial banking sectors. In the final section the paper conclude the results which provide meaningful insight into the structuring and interconnectedness of the EU banking sector.

2. Literature review

There have been extensive researches about the failure in the financial institution area since late 1960s. A variety of multivariate methods and other techniques have been applied to solve bankruptcy prediction problem in banks and firms. While, some of the literature researches try to measure the movements between the EU banks. Their findings support that EU-wide macroeconomic and banking specific shocks are significant and that some risks have increased since EMU.2 for example, Chapters 6 and 7, De Nicolo and others (2005), and Brasili and Vulpes (2005). Gropp and Moerman (2003) focus on contagion to identify 12 systemically important banks in Europe. They show that significant contagious influence emanates from some smaller EU countries. Evans et. al. (2008) reports that the banking sector deregulation at the national level and the opening markets to international competition caused convergence for the banking industry's' main indicators of bank profitability or earning patterns, but not their asset-liability related ratios. Decreasing et al.(2007) mentions that financial institutions should yield better risk profiles by increasing diversification both of their internationally and across different business lines. However, if the diversification is made by institutions in the same way this can lead bigger shocks or increase fragility.

Detecting potential risks and vulnerabilities in national financial systems and resolving instabilities if and when they arise are likely to require a strong cross-border perspective. Gropp, Vesala, and Vulpes (2002) used cluster analysis for euro area banks to analyze the banking sector fragility, and demonstrated its usefulness as a complement to traditional balance-sheet-based analysis of risks. For large, complex financial institutions of both the United States and Europe, Hawkesby, Marsh, and Stevens (2002) applied agglomerative hierarchical cluster analysis to the data in order to explore the network structure of the companies. Alam, Booth, and Thordason (2000) found that clustering algorithm and self-organizing neural networks approaches provide valuable information to identify potentially failing banks.

Cluster and Factor Analysis of Structural Economic Indicators for Selected European Countries (2009), used cluster analysis on three structural economic indicators: GDP per capita, total employment rate and comparative price levels to classify Croatia and EU 27 Member States according to the structural economic indicators. According to the results of the Ward's method and three chosen structural economic indicators Croatia was classified along with the following EU Member States: Bulgaria, Hungary, Poland, Romania, Slovakia and Malta.

Forte and Santos (2015) used hierarchical clustering method with squared Euclidean distance to examine the FDI performance of Latin American countries. The cluster with better FDI performance (Chile, Panama, Uruguay, and Costa Rica) also performs better in terms of variables such as market size, trade openness, and human capital. Dardac and Boitan (2009) used Cluster Analysis, as an exploratory technique in order to include a representative sample of Romanian credit institutions into smaller, homogenous clusters, to assess which credit institutions have similar patterns according to their risk profile and profitability.

3. Data

The sampling data in this study comprised of consolidate data from 26 countries in the European Union (EU) zone. Which covers the sampling period from 2008 to 2013 which included the following countries: Austria, Belgium, Bulgaria, Cyprus, Czech Republic, Germany, Denmark, Estonia, Spain, Finland, France, United Kingdom, Greece, Hungary, Ireland, Italy, Lithuania, Luxembourg, Latvia, Netherlands, Poland, Portugal, Romania, Sweden, Slovenia, and Slovakia. Croatia has been exclude from the study due to the late addition to the EU as well as lack of available consolidated data. The study excluded Malta into the sampling population of the EU countries, this is due to the fact that Malta was shown as the outlier for in all the results.

The selection of variables is naturally an important factor in the composition of clusters (Table 1). When the aim of the analysis is broad enough, as is the case here, the number of candidate instruments increases. In parallel with this condition five banking indicators which are commonly used in the literature are selected to cluster the banking system. They are leverage percentage, Return on Asset, Tier 1 capital, Capital requirement percentage, Equity to asset ratios. Prior to the selection of the variables used in the analysis, test for correlation between the variables have been carried out to remove highly correlated variables, Such as Return of Asset and Return on Equity were highly correlated. The following table provides a short description of the variables used in this analysis.

Table 1 Description of the variables

Variables	Descriptions
Leverage Percentage	Percentage of bank's lending (debt) to the value of its ordinary share of equity in percentage
Return on Assets	Bank's annual earning divided by total assets, sometimes referred as return on investment
Tier 1 capital	Capital adequacy requirement of a bank, consists of primary of common stock or core capital and disclose reserves
Capital requirement percentage	Standard capital requirement for banks, which determine the liquidity and
Equity to asset ratios	Ratio of total assets of the banks in proportion to the bank's equity

Source: own construction

Unfortunately due to the lack of data, some variables which can be useful for the further research have been excluded as well. Variables are comprised of annual banking sector indices available from European Central Bank (ECB) for the sample period of six financial years (2008 to 2013). These open sources banking sectors indices are constructed by the European Central Bank, these indices are contrasted based on the domestic banks, stand-alone banks, foreign banks and controlled subsidiaries of foreign countries branches of each EU countries. Unfortunately the data set has some missing values, we have adopted the approach to solve the missing data problem using the estimated value replacement approach.

4. Methodology

Cluster analysis is a technique that identifies the complex relationships between variables, without imposing any restriction. Therefore, the input dataset doesn't need the distinct specification of an explanatory variable (the dependent variable) and respectively, of predictor ones (independent variables). There is no difference between the level of importance of the variables, the aim of the analysis is not to predict a certain value, but, to provide some clear view for the presence of specific patterns or correlations among variables, to include the different variables or cases into more homogenous groups (Dardac − Boitan 2009). Cluster analysis can be used to explore the hierarchical structure of a system and that does not only provides an intuitive picture of the linkages of the system, but also displays meaningful cluster. Cluster analysis which groups (clusters) so that objects from the same cluster are more similar, with respect to a given attribute, to each other than objects from different clusters is a common technique for statistical data analysis in many fields, such as machine learning, pattern recognition, and bioinformatics (Khashanah − Miao 2011).

Cluster analysis is a useful method for examining complex relationships among national characteristics and international linkages without imposing any a priori restrictions on these interrelationships. Cluster analysis became a very popular tool to analyse a large amount of complex data, such as in the analysis of the banking sector (Sørensen − Puigvert Gutiérrez 2006).

This study employs a Hierarchical Cluster Analysis to identify the clusters in EU Banking Sector. Leverage, ROA, Tier 1, Capital requirement, equity/asset ratios have been selected as the variables to observe the similarities of the countries. This analysis consists of assessing whether the crisis has promote the similarity in pattern of the banking sectors in the euro area countries. In this respect, we use a hierarchical cluster analysis by considering two sub-periods: a “pre-crisis” (1999–2007) and a “crisis” period (2008–11). Hierarchical cluster analysis provides a unique set of grouped categories or clusters by sequentially pairing variables, clusters, or variables and clusters. Starting with the correlation matrix, all clusters and uncluttered variables are tried in all possible pairs at every step. The pair with the highest average inter-correlation within the trial cluster is chosen as the new cluster. On the other hand, in the other types of cluster analysis a single set of mutually exclusive and exhaustive clusters is formed whereas hierarchical method all variables are clustered in a single group starting from a larger cluster by getting tighter in each step (Bridges 1966).

In our analysis algorithm starts by considering that each country forms its own cluster, in the following stage the countries with similar data are grouped into the same cluster. Next phase is adding a new country or forming a two-country cluster. The process continues until all the countries are the same cluster. Finally, the outcomes summarized in a cluster tree called dendrogram, which represents the different steps of agglomeration described above. Cutting branches off the dendrogram allows to determine the optimal number of clusters, and therefore the degree of heterogeneity of our sample. The first step of the analysis consists of measuring the distance or dissimilarity between every pair of countries, defined here by the Euclidean distance:

$$d^2(i,l) = \sum_{k=1}^{K} (x_{ik} - x_{lk})^2 \tag{1}$$

Variables have been standardised to avoid the variances in scale which lead to a greater impact on the clustering of our data. The Euclidean distance is measured from the variable from each of the EU Countries. The grouping and the linkage of the cluster are formed based on the distance matrix computed. Though there are several technique to determine the linkage of the cluster, we have adopted the most commonly used method of Ward (Ward 1963), this method is computed based on the multidimensional variance, including total variance and decomposed variance:. The total variance can be decomposed into the between and within the variance:

$$\sum_{k=1}^{K}\sum_{q=1}^{Q}\sum_{i=1}^{I_q}(x_{iqk} - \bar{x}_k)^2 = \sum_{k=1}^{K}\sum_{q=1}^{Q} I_q(\bar{x}_{qk} - \bar{x}_k)^2 + \sum_{k=1}^{K}\sum_{q=1}^{Q}\sum_{i=1}^{I_q}(x_{iqk} - \bar{x}_{qk})^2 \tag{2}$$

x_{iqk} as the value of variance for the variable K for the country within the cluster q

$\bar{x}_{qk}$ the mean of the variable K for the country within the cluster q

$\bar{x}_k$ Overall mean of variable K, and Iq is the number of the countries in the cluster q

Based on this decomposition, a good agglomeration will minimize the within cluster variance and maximize the between variance. Minimal increase in variance means that the linked clusters are relatively similar. The term of Euclidean distance can be written as:

$$\Delta(p,q) = \frac{I_p I_q}{I_p + I_q} d^2(c_p, c_q) \tag{3}$$

I_p number of countries in the cluster p

I_q number of countries in the cluster q

c_p and c_q the centroid of the clusters p and q

The Ward algorithm are the linking of two clusters, the increase of ($\Delta(p,q)$) is the smallest. Repetitively, the centroid of each cluster is based on the country assigned to the cluster, hence the distance matrix is recomputed, and the algorithm is repeatedly computed until all the countries are agglomerated into a single cluster. In this case the clustering is performed for 2008-2013. For each variable, the missing value is replaced with estimated means. The results of the hierarchical clustering are discussed in the next section.

5. Results

The dendrograms for the 2008–2013 periods are providing a wide vision about the clusters of the European banking sector. In each dendrogram, the vertical axis represents countries in the EU, and the horizontal axis illustrates differences between countries. Vertical lines in the dendrogram indicate the linkage of two countries or clusters. Countries that are similar to each other are combined at low heights, whereas countries that are showing differences are combined higher up the dendrogram. Therefore, if the link between the countries are at a higher point, it means that the dissimilarity between countries or clusters is the greater.

From the dendrograms Table 1 has been created to illustrate the clusters in an easy way to be understood. According to the table each colour on each year shows a different cluster. The fact that are no perfect clustering results, especially with a bigger data set, our results have exhibit that some of the clusters are close to each other's, therefore, we place the cutting the tree at 0-10 in order to determine the most relevant grouping and a method to cluster the larger set of data.

Table 1 shows the clusters of this study. Although there are some changes in the members of groups, there are 3 clusters in all years. The cluster are shown with different colours to make it easier to realize the differences. Blue cluster is generally including south European countries and Austria. Brown cluster mostly contains bigger economies of the EU such as UK, Germany, and France. And the grey cluster includes generally Eastern European countries and Baltic countries.

The cluster in which Greece was placed has showed a change after 2010, and their ratios become similar to the blue cluster which includes biggest economies in the EU zone. But in general Western countries and Eastern countries have their own groups and the changes between these groups can hardly be seen.

The last but not the least, as we observed there is no decrease in the number of the clusters over the years. This explains that integration of the banking sector ratios in the EU is very limited. Even though there are new mergers, the heterogeneity of the banking sector stayed stable between 2008 and 2013.

Table 2 Comparison of the banking clusters from 2008 to 2013

	CLUSTER1
	CLUSTER2
	CLUSTER3

COUNTRY	2013	2012	2011	2010	2009	2008
Austria	Austria	Austria	Austria	Austria	Austria	Austria
Belgium	Cyprus	Belgium	Cyprus	Cyprus	Belgium	Cyprus
Bulgaria	Spain	Germany	Spain	Estonia	Cyprus	Spain
Cyprus	Hungary	Denmark	Hungary	Greece	Germany	Greece
Czech Republic	Italy	Spain	Italy	Hungary	Denmark	Italy
Germany	Portugal	Finland	Portugal	Italy	Spain	Portugal
Denmark	Slovenia	France	Slovenia	Lithuania	Finland	Belgium
Estonia	Belgium	UK	Belgium	Latvia	France	Germany
Spain	Germany	Italy	Germany	Portugal	UK	Denmark
Finland	Denmark	Netherlands	Denmark	Romania	Greece	Finland
France	Finland	Portugal	Finland	Slovenia	Ireland	France
UK	France	Sweden	France	Belgium	Italy	UK
Greece	UK	Slovenia	UK	Germany	Luxembourg	Ireland
Hungary	Greece	Bulgaria	Greece	Denmark	Netherlands	Luxembourg
Ireland	Ireland	Czech Republic	Ireland	Spain	Portugal	Netherlands
Italy	Luxembourg	Estonia	Luxembourg	Finland	Sweden	Sweden
Lithuania	Netherlands	Hungary	Netherlands	France	Slovenia	Bulgaria
Luxembourg	Sweden	Ireland	Sweden	UK	Bulgaria	Czech Republic
Latvia	Bulgaria	Lithuania	Bulgaria	Ireland	Czech Republic	Estonia
Netherlands	Estonia	Luxembourg	Czech Republic	Luxembourg	Hungary	Hungary
Poland	Lithuania	Latvia	Estonia	Netherlands	Poland	Lithuania
Portugal	Latvia	Poland	Lithuania	Sweden	Romania	Latvia
Romania	Poland	Romania	Latvia	Bulgaria	Slovakia	Poland
Sweden	Romania	Slovakia	Poland	Czech Republic	Estonia	Romania
Slovenia	Slovakia	Cyprus	Romania	Poland	Lithuania	Slovenia
Slovakia	Czech Republic	Greece	Slovakia	Slovakia	Latvia	Slovakia

Source: own construction

6. Conclusion

This paper analysed the EU banking sector by using a hierarchical cluster analysis. The results obtained help us to observe that there are some dissimilarities between the EU countries in terms of banking structure. Although working under the same authority and similar governing policies, the regulators hope to create the fair and competitive market for all financial institutions. Some of the very important ratios of the EU banking system proven to be differentiated in many countries. The findings of our analysis support that the countries in the same neighbourhood and with higher economic partnership tend to stay in the same cluster. As an example Sweden and Denmark; Portugal, Spain and Italy; Cyprus and Greece; Latvia, Lithuania, Slovenia, Czech Republic and Poland; Romania, Hungary and Austria clustered in their own groups throughout 2008 to 2013. The characteristic of their banking system are therefore similar based on the financial ratios.

On the other hand, the level of development and cooperation between countries cause them to be clustered in the same group: UK, France and Germany are mostly clustered together with a few years' exceptions.

Southern European countries have had problems during and after the mortgage crisis started in the US and diffused in Europe. Especially Greece has faced serious difficulties in the aftermath of the crisis. There has been changes in the banking policies and mergers due to the problems and this can be the main reason for the cluster change.

The foreign ownership of the banks in many countries affect the clusters. Although some banks try to follow country specific policies, generally the ratios are similar to the mother country ratios.

As Decreasing et. al. (2007) stated that geographic diversification leads to different investment strategies, as some banks are heavily invested in the new member states, while others follow a worldwide or more domestically oriented strategy. Similar with the conclusion of this study, the findings of our research could be eminent for the policy makers of the current and extended EU member and for the candidate countries, suggest that being a part of the EU does not mean that all the countries show similar changes or characteristics.

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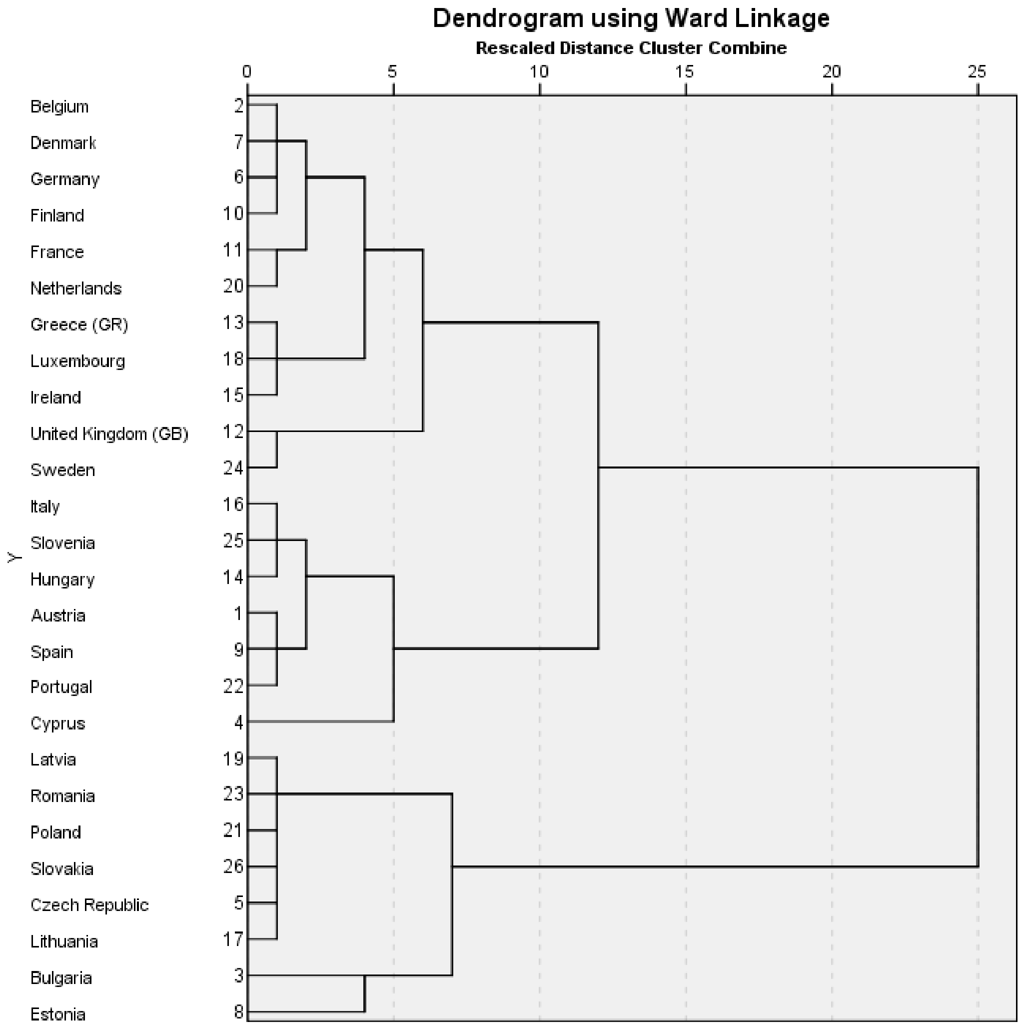
Appendix

Appendix 1 Cluster dendrogram and memberships (2013)

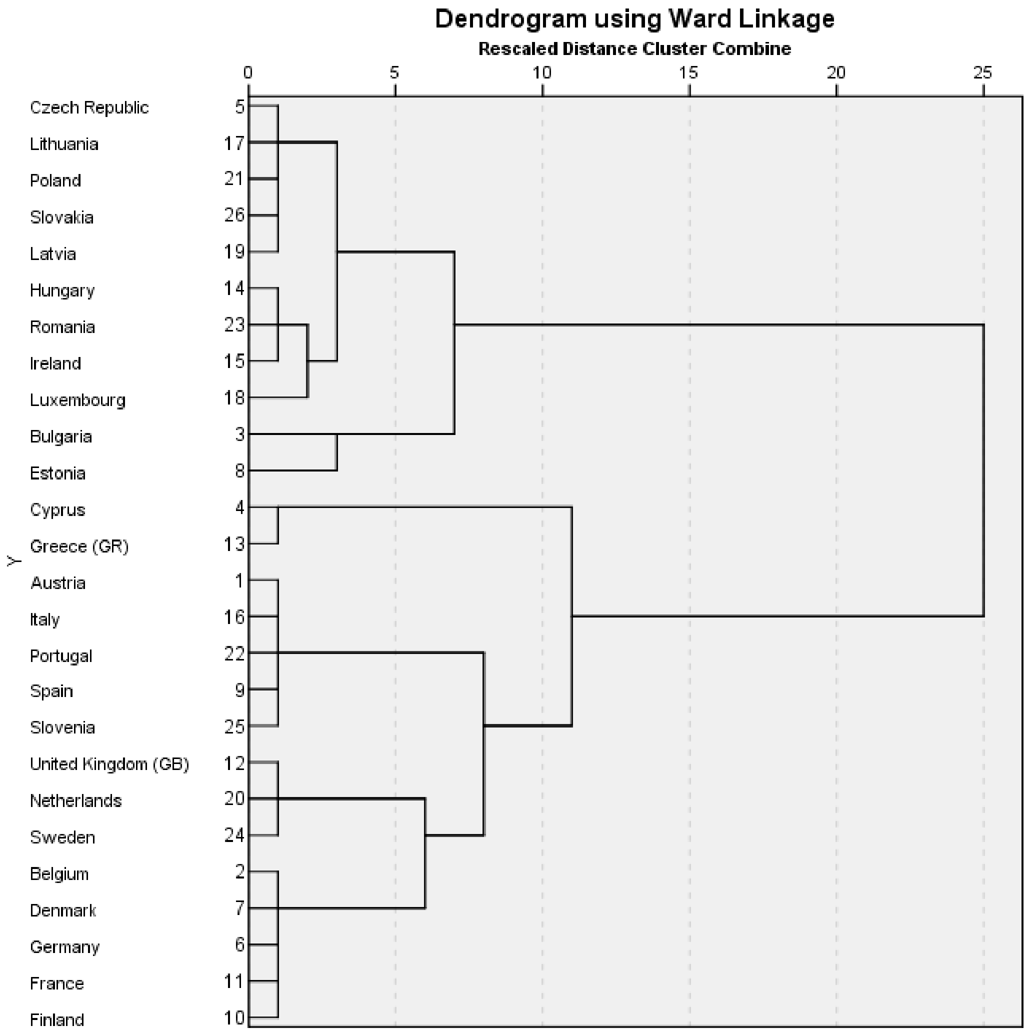


Cluster Membership

Case	3 Clusters
1:Austria	1
2:Belgium	2
3:Bulgaria	3
4:Cyprus	1
5:Czech Republic	3
6:Germany	2
7:Denmark	2
8:Estonia	3
9:Spain	1
10:Finland	2
11:France	2
12:United Kingdom (GB)	2
13:Greece (GR)	2
14:Hungary	1
15:Ireland	2
16:Italy	1
17:Lithuania	3
18:Luxembourg	2
19:Latvia	3
20:Netherlands	2
21:Poland	3
22:Portugal	1
23:Romania	3
24:Sweden	2
25:Slovenia	1
26:Slovakia	3

Source: own construction

Appendix 2 Cluster dendrogram and memberships (2012)

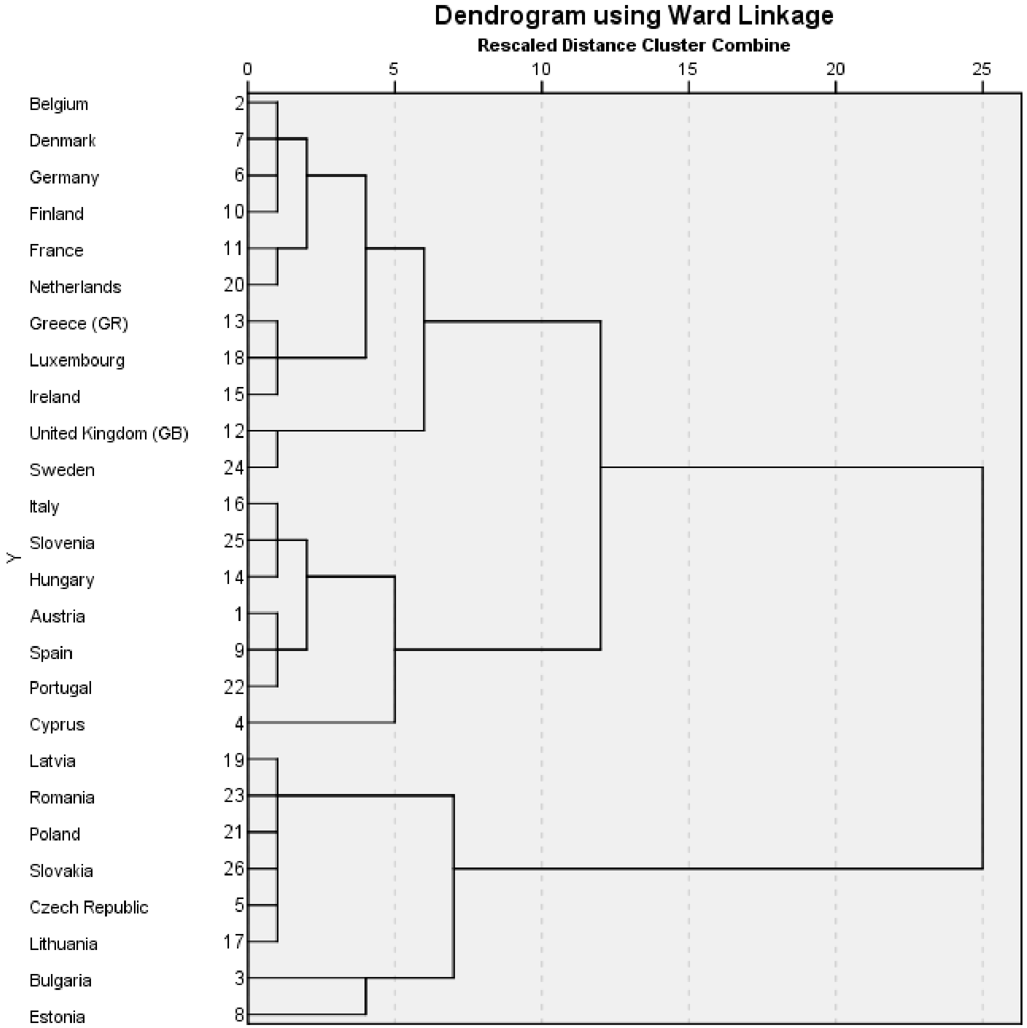


Cluster Membership

Case	3 Clusters
1:Austria	1
2:Belgium	1
3:Bulgaria	2
4:Cyprus	3
5:Czech Republic	2
6:Germany	1
7:Denmark	1
8:Estonia	2
9:Spain	1
10:Finland	1
11:France	1
12:United Kingdom (GB)	1
13:Greece (GR)	3
14:Hungary	2
15:Ireland	2
16:Italy	1
17:Lithuania	2
18:Luxembourg	2
19:Latvia	2
20:Netherlands	1
21:Poland	2
22:Portugal	1
23:Romania	2
24:Sweden	1
25:Slovenia	1
26:Slovakia	2

Source: own construction

Appendix 3 Cluster dendrogram and memberships (2011)

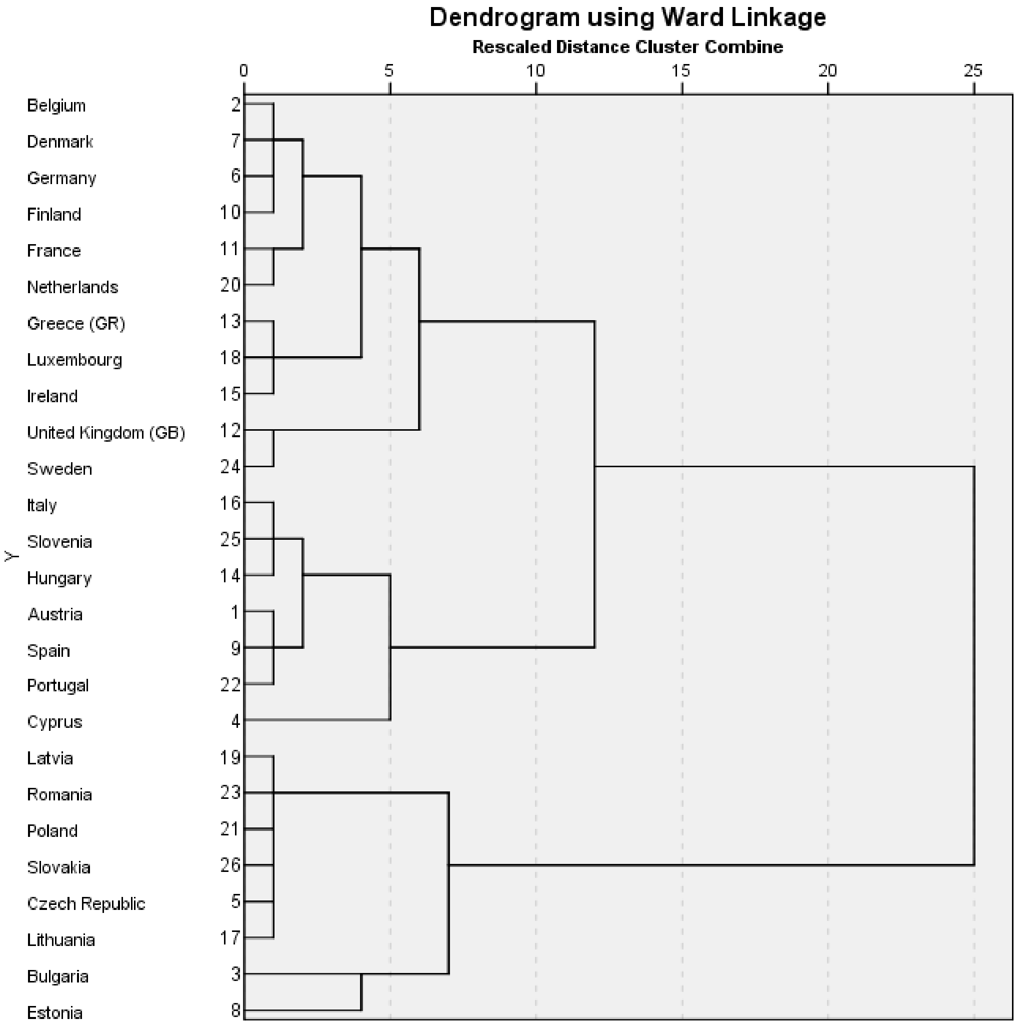


Cluster Membership

Case	3 Clusters
1:Austria	1
2:Belgium	2
3:Bulgaria	3
4:Cyprus	1
5:Czech Republic	3
6:Germany	2
7:Denmark	2
8:Estonia	3
9:Spain	1
10:Finland	2
11:France	2
12:United Kingdom (GB)	2
13:Greece (GR)	2
14:Hungary	1
15:Ireland	2
16:Italy	1
17:Lithuania	3
18:Luxembourg	2
19:Latvia	3
20:Netherlands	2
21:Poland	3
22:Portugal	1
23:Romania	3
24:Sweden	2
25:Slovenia	1
26:Slovakia	3

Source: own construction

Appendix 4 Cluster dendrogram and memberships (2010)

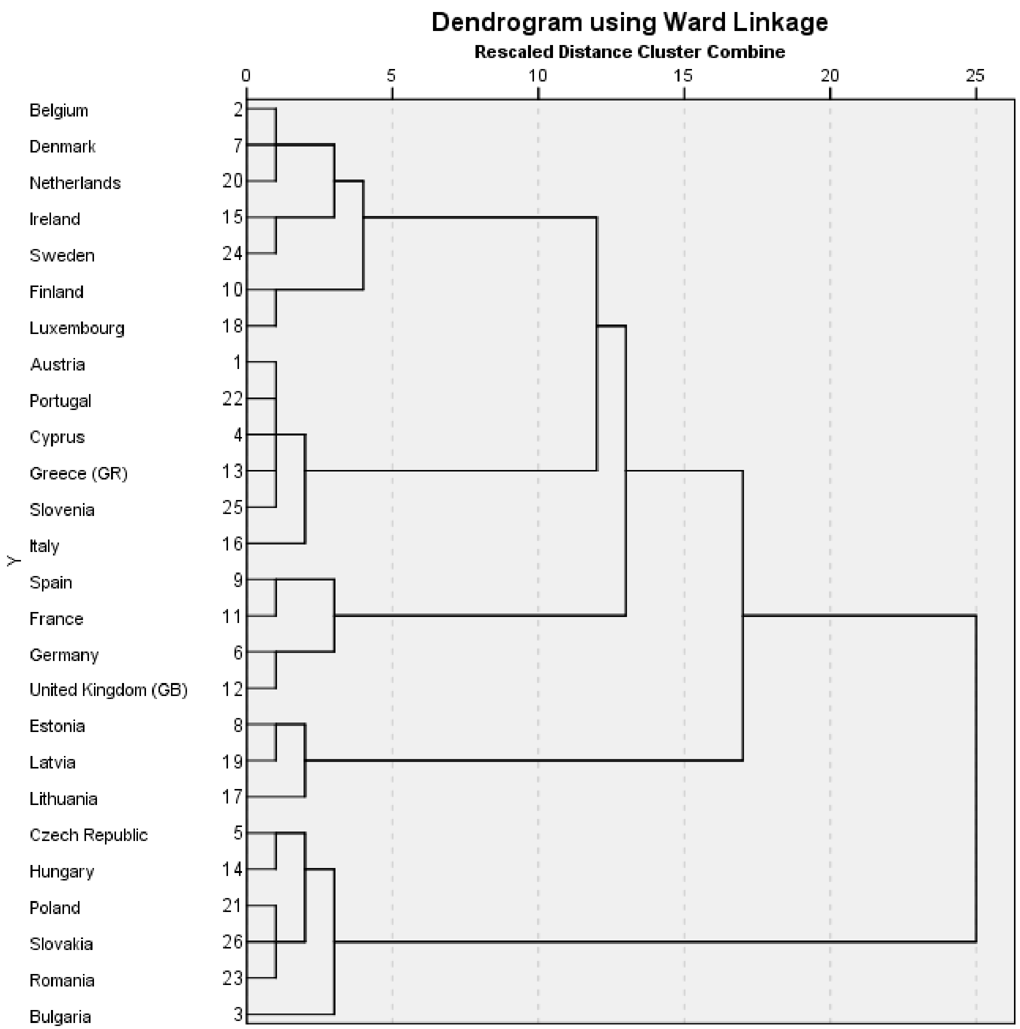


Cluster Membership

Case	3 Clusters
1:Austria	1
2:Belgium	2
3:Bulgaria	3
4:Cyprus	1
5:Czech Republic	3
6:Germany	2
7:Denmark	2
8:Estonia	1
9:Spain	2
10:Finland	2
11:France	2
12:United Kingdom (GB)	2
13:Greece (GR)	1
14:Hungary	1
15:Ireland	2
16:Italy	1
17:Lithuania	1
18:Luxembourg	2
19:Latvia	1
20:Netherlands	2
21:Poland	3
22:Portugal	1
23:Romania	1
24:Sweden	2
25:Slovenia	1
26:Slovakia	3

Source: own construction

Appendix 5 Cluster dendrogram and memberships (2009)

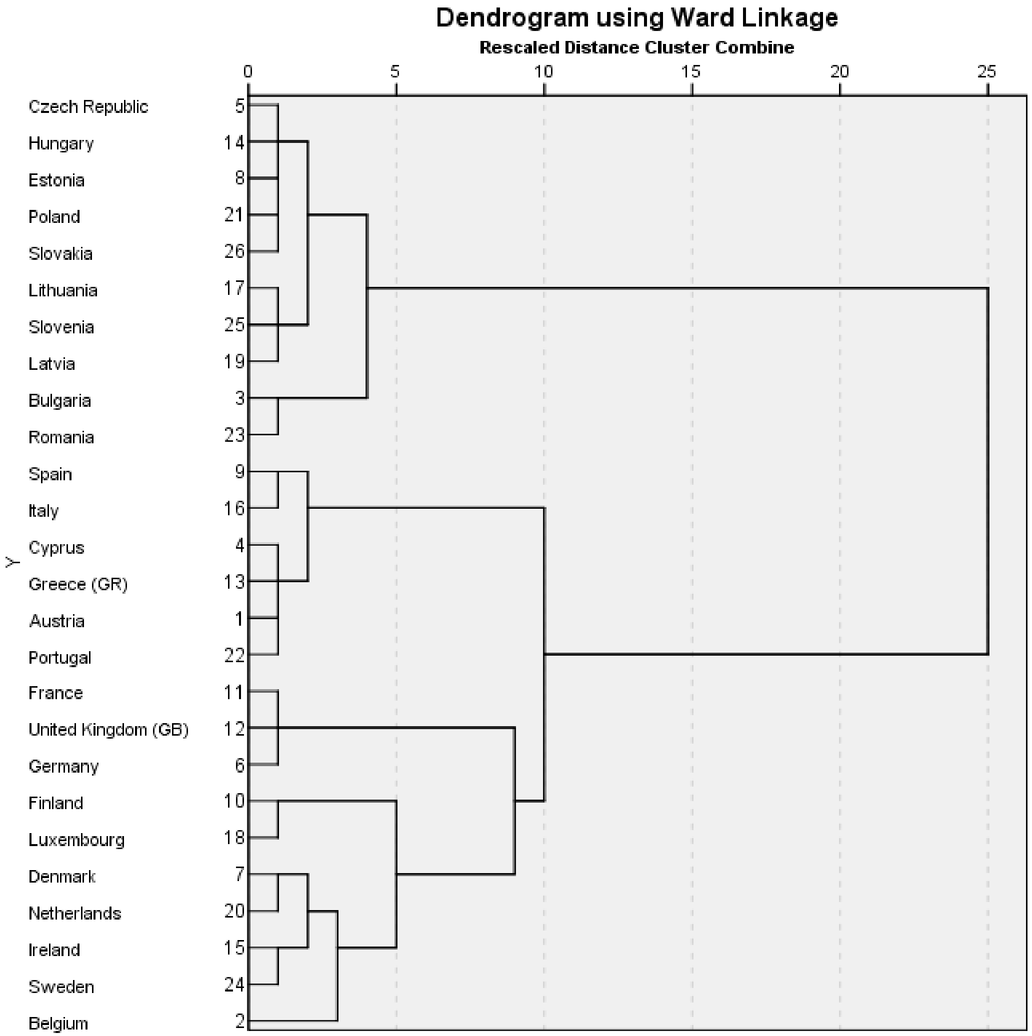


Cluster Membership

Case	3 Clusters
1:Austria	1
2:Belgium	1
3:Bulgaria	2
4:Cyprus	1
5:Czech Republic	2
6:Germany	1
7:Denmark	1
8:Estonia	3
9:Spain	1
10:Finland	1
11:France	1
12:United Kingdom (GB)	1
13:Greece (GR)	1
14:Hungary	2
15:Ireland	1
16:Italy	1
17:Lithuania	3
18:Luxembourg	1
19:Latvia	3
20:Netherlands	1
21:Poland	2
22:Portugal	1
23:Romania	2
24:Sweden	1
25:Slovenia	1
26:Slovakia	2

Source: own construction

Appendix 6 Cluster dendrogram and memberships (2008)



Cluster Membership

Case	3 Clusters
1:Austria	1
2:Belgium	2
3:Bulgaria	3
4:Cyprus	1
5:Czech Republic	3
6:Germany	2
7:Denmark	2
8:Estonia	3
9:Spain	1
10:Finland	2
11:France	2
12:United Kingdom (GB)	2
13:Greece (GR)	1
14:Hungary	3
15:Ireland	2
16:Italy	1
17:Lithuania	3
18:Luxembourg	2
19:Latvia	3
20:Netherlands	2
21:Poland	3
22:Portugal	1
23:Romania	3
24:Sweden	2
25:Slovenia	3
26:Slovakia	3

Source: own construction

Appendix 7 Changes in cluster memberships

2012

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1	13	.1	50.0	50.0
	2	11	.1	42.3	92.3
	3	2	.0	7.7	100.0
	Total	26	.2	100.0	
Missing	System	16355	99.8		
Total		16381	100.0		

2013

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1	7	.0	26.9	26.9
	2	11	.1	42.3	69.2
	3	8	.0	30.8	100.0
	Total	26	.2	100.0	
Missing	System	16355	99.8		
Total		16381	100.0		

2011

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1	7	.0	26.9	26.9
	2	11	.1	42.3	69.2
	3	8	.0	30.8	100.0
	Total	26	.2	100.0	
Missing	System	16355	99.8		
Total		16381	100.0		

2010

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1	11	.1	42.3	42.3
	2	11	.1	42.3	84.6
	3	4	.0	15.4	100.0
	Total	26	.2	100.0	
Missing	System	16355	99.8		
Total		16381	100.0		

2009

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1	17	.1	65.4	65.4
	2	6	.0	23.1	88.5
	3	3	.0	11.5	100.0
	Total	26	.2	100.0	
Missing	System	16355	99.8		
Total		16381	100.0		

2008

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1	6	.0	23.1	23.1
	2	10	.1	38.5	61.5
	3	10	.1	38.5	100.0
	Total	26	.2	100.0	
Missing	System	16355	99.8		
Total		16381	100.0		

Source: own construction