17. TRENDS OF THE CONTAGION RISK IN SOVEREIGN SPREADS FOR EMERGING EUROPEAN COUNTRIES

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Abstract

We investigate the sovereign spreads behavior of the European emerging countries using the clustering technique. Our main finding is that the distances between spreads during high volatile times is significantly lower than in normal periods, that is, the correlation is much higher. Secondly, the market sentiment explains a much higher percentage of the spreads movements during turbulent times. Thirdly, the link between spreads and macroeconomic fundamentals seems to be blurred compared with the expectations from the economic theory.

Keywords: contagion spreads, emerging markets, clustering

JEL Classification: C14, G15, F37

1. Introduction

The informational content from the sovereign securities issued by the emerging countries raised its usefulness in the last decade. Starting in early 1990s, bonds have surpassed bank loans dynamics in net financing the emerging markets. This process was encouraged after the "tequila" crisis, by the sovereign debt restructuring (loan conversion to Brady bonds). The emerging Europe is less represented in the global financial markets, but its issuance increased in the latest years. The outstanding amount of sovereign bonds[1] from this region increased by 75% during Q1/2004 - Q3/2008, to USD 217 billion (IMF, SDDS database[2]).

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[1] The countries included here are: Romania, Estonia, Latvia, Lithuania, Russia, Ukraine, Croatia, Slovenia, Slovakia, the Czech Republic, Hungary, Turkey, and Poland.
[2] Bulgaria and Iceland are not included due to lack of data.

The sovereign bonds spreads were considered one of the handiest tools for assessing a country risk profile. Howbeit, the developments from the current financial crisis raise the question of their usefulness in the light of rising risk aversion and liquidity issues that affected both the (emerging bond) market and the investors (also known as funding liquidity risk).

The literature is rich in articles using different parametric techniques to explain the main drivers of the sovereign spreads. In this paper we follow another avenue. We employ two non-parametric approaches (clustering and principal components) to investigate the patterns for the spreads co-movements. We also test if theory findings explain these movements.

We try to answer the following questions: (i) Has a rating upgrade or an EU membership prospective changed the investors' perception about pricing a CEE country sovereign bond (or would that specific country still remain in the investors' mind along with its former cluster colleagues that have not faced changes in ratings or EU membership)?; (ii) Is there any link between the macroeconomic characteristics of CEE countries and the way the spreads are clustered?; and (iii) Is there a change in how investors evaluate the risk profile of a country during high volatility periods compared with tranquil times?

The spreads used in this paper are computed as relative yield difference over German similar issuance[3] (Annex 4). The criteria for selecting bonds are: (i) to be traded on the Bloomberg platform; (ii) with no specific option features attached to the issue and no inflation rate adjustments; (iii) with an outstanding amount of over USD 250 million; (iv) and with the remaining maturity of at least five years. The first and third criteria are a minimum condition for a liquid market, while the last one allows us to analyze the spread in two different market conditions (e.g., pre-crisis vs. crisis, pre-accession vs. post-accession, etc.). Another argument for the last condition is that the 10-year issuance is the highest tender most of the developing countries have on the international markets. The data sources for the macroeconomic and financial framework of the emerging countries are WEO, BIS, IFS-IMF and ECB. The tenure analyzed is 2004-2009.

The structure of the paper is the following: the next section briefly discusses the main literature findings; section three presents the clustering methods and the principal component analysis, section four highlights the results and the last section concludes.

2. Literature review

While there is a wide acceptance that fundamentals do matter in spreads behavior, the empirical evidence shows they explain a small part only. Moreover, spreads tend to be depressed during times of high liquidity, as investors are more risk-tolerant

[3] Eichegreen and Mody (1998) argue that primary market prices are more informative from the issuer's point of view as it reflects better its risks, but given the low issuance of Central and East European countries (CEEs) (Romania had only one issuance in 2008), the secondary market prices will serve our purpose. We keep in mind that the liquidity risk plays a bigger role in these countries.

(Powell and Martinez, 2008) [4]. Ferrucci (2003) finds similar results analyzing the period prior to the 1997 Asian crisis.

One theory that accounts for this disconnection between spreads and fundamentals is based on the cost of information. Calvo and Mendoza (2000) argue that in the context of integrated financial markets, the investor faces a tradeoff between portfolio diversification and well informed trades, as the cost of acquiring in-depth analysis is a fixed cost with no regard to the amount invested. In turbulent times, the spreads are affected by herding behavior, investors pricing the countries risk based on superficial characteristics (Chari and Kehoe 1997).

Another theory takes into accounts the difficulties in diversifying the credit risk (Amato and Remolona, 2003). Spreads can be seen as a sum of two components: (i) the premium requested as a compensation for expected loss from sovereign default; and (ii) the risk premium, the additional compensation for the unexpected loss. Remolona, Scatigna and Wu (2007) show that the first term tends to play a much smaller role, while the second one, known as the price of risk or the "credit spread puzzle" is much more variable and tend to be countercyclical.

The ratings are another determinant[5] of spreads as they contain the information regarding the fundamentals and their development on long term. Powell and Martinez (2008) take into account that ratings contains also the projections over fundamentals and find evidence that ratings matter for spreads above fundamentals. Kaminsky and Schmukler (2001) study the implications of ratings announcement for spreads dynamics. Their findings do not prove the strong efficiency hypothesis as markets tend to incorporate the rating changes sooner than the announcement day, i.e. investors with privileged positions (better information access or even in possession of private information) can make abnormal profits in sovereign bond market.

Apart from fundamentals, ratings and political risk[6], another important determinant of spreads dynamics is the market sentiment. McGuire and Schrijvers (2003) find that common factors are responsible for one third of the total daily variation, with the first factor accounting for more than 80% of the total common variation. This factor is considered to reflect the investors' attitude towards risk.

3. Cluster methods

The cluster analysis consists in identifying the groups or classes within the data according to different criteria. The number of classes can be predefined or it can result

[4] Luengnaruemitchai and Schadler (2007) argue that CEEs' sovereign yields were compressed in the pre-crisis period, as they mostly reflected the optimistic expectations of income convergence after entering the European Union, and not the current fundamentals.

[5] See also Hördahl and Packer (2007) for a more detailed overview of the literature on spreads.

[6] Moser (2007) analyzes the political risk effects on sovereign bond spread of Latin American countries in 1997-2007 and finds that uncertainty about the future course of economic policy increases financing costs for these countries. Even more, a minister change is almost always preceded (for one month and a half) by a significantly upward trend in spreads and it is followed by another one month and a half of high, but stable spreads.

from the analysis based on the desired degree of homogeneity within the classes. There are two methods of clustering: hierarchical and partitioning (or k-means). The first step is to calculate the distance (similarity) between objects into the "n" dimensional space (each dimension being one characteristic or criterion of the objects). The distances for the given matrix $X_{(m*n)}$ – the m objects with n characteristics – are described by $D_{(m*m)}$ matrix. The greater the distances between objects, the smaller the similarity between them, the less likely to be in the same group. The distance for continuous variables (as in our case) can be measured on a wide variety of L_r norms, r≥1[7].

$$d_{ij}^1 = \left\|x_i - x_j\right\|_r \Leftrightarrow d_{ij}^1 = \left\{\sum_{k=1}^{n}\left|x_{ik} - x_{jk}\right|^r\right\}^{1/r} \quad (1)$$

Another option for measuring the similarities between objects is to use the correlation coefficient defined by:

$$d_{ij}^1 = 1 - \frac{(x_i - \overline{x_i})(x_j - \overline{x_j})^T}{[(x_i - \overline{x_i})(x_i - \overline{x_i})^T]^{0.5}[(x_j - \overline{x_j})(x_j - \overline{x_j})^T]^{0.5}} \quad (2)$$

The second stage consists in grouping the objects based on these distances, according to a chosen algorithm. There are two main types of algorithms used: hierarchical and k-means. The hierarchical algorithms can be agglomerative, starting with clusters containing only one item and then grouping them, or they can be splitting, which starts from the opposite point: the first cluster contains all the items and then it splits them to the optimal size. The k-means method starts with a predefined number of clusters and it changes their composition until it reaches an accepted level of performance. The distances between classes are calculated based on the formula (Härdle and Simar 2007):

$$d(P, R+Q) = \partial_1 * d(P,R) + \partial_2 * d(P,Q) + \partial_3 * d(P,Q) + \partial_4 * |d(R,P) - d(R,Q)| \quad (3)$$

where: ∂_i, i={1,2,3,4} differs according to one of the methods: single, complete, average, weighted, centroid, median, ward.

In this study we mainly use the ward distance (based on the cophenetic correlation test – see below):

$$\partial_1 = \frac{n_r + n_p}{n_r + n_p + n_q}; \partial_2 = \frac{n_r + n_q}{n_r + n_p + n_q};\ \partial_3 = -\frac{n_r}{(n_r + n_p + n_q)^2};\ \partial_4 = 0; (4)$$

To select the algorithm for grouping data into samples we used the cophenetic correlation test (Sokal and Rohlf 1962):

[7] An underlying assumption in applying distances based on L_r norms is that the variables are measured on the same scale; if not, then standardization should be applied.

$$\frac{\sum_{i<j}(d_{ij}^1 - d^1)(d_{ij}^2 - d^2)}{\sqrt{\sum_{i<j}(d_{ij}^1 - d^1)^2 \sum_{i<j}(d_{ij}^2 - d^2)^2}} \quad (5)$$

where: d^1_{ij} represents the distances calculated in the first stage, d^2_{ij} in the second, and the d^1 and d^2 being the mean distances of those.

This test checks the consistency of the distances between groups and objects, as we should expect to have smaller distances between objects (the lower part of the dendrogram chart) and higher distances between groups (the upper part of the dendrogram chart), thus a higher value means a better estimation.

To determine the optimum number of clusters we use a silhouette indicator, defined as:

$$S(i) = \frac{\min(b_{i,k}) - \min(a_i)}{\max(a_i, \min(b_{i,k}))} \quad (6)$$

where: a_i is the average distance between point i and the other points from the same cluster, and $b_{i,k}$ is the average distance between the point i from one cluster to points in cluster k.

The test measures the ratio of the differences between the minimum distances between clusters and the minimum distance within the cluster, and the maximum of the two. A higher value gives a better estimate.

Principal component analysis consists in projecting the original data on a subspace in which the data approximately lie down, therefore without losing too much of the accuracy. The method can be used (i) to reduce the dimensions of the data; or (ii) to determine the structure of the data.

Given the initial data matrix, $X_{(m*n)}$, where m represents the number of variables and n the number of observations, the aim is to find the first unit vectors, $u_{k,\ k<m}$, for which the projected data have the largest variance (also known as the major axes of variations):

- the length of projection of x onto u is $x^T u$
- the variance of the projection is

$$\frac{1}{m}\sum_{i=1}^{m}[x_i^T u]^2 = \frac{1}{m}\sum_{i=1}^{m} u^T x_i x_i^T u = u^T \left[\frac{1}{m}\sum_{i=1}^{m} x_i x_i^T\right] u = u^T \Sigma\, u \quad (7)$$

The objective is to maximize the variance. This is equivalent to finding the first k (k<m) eigenvectors ($u_{1,2..k}$) of variance-covariance matrix, ∑.

$$\Sigma u = \lambda u \quad (8)$$

The original dataset, $X_{(m*n)}$, can be re-written in the $u_{1,2..k}$ space as $Y_{(n*k)}$ (or principal components):

$$Y = X^T\,[u_1\, u_2 \ldots u_k] \quad (9)$$

Results

For answering the first question (i.e. a rating upgrade or an EU membership prospective changed the investors' perception about pricing a CEE country sovereign bond), we compare the results from the clustering analysis conducted on different periods and to investigate for differences (details in Annex 1). If the rating upgrades and/or EU membership status are perceived as important changes in country capacity to fulfill the debt obligations, this should be reflected in higher differences between spreads of such countries compared with countries that did not receive EU membership or investment grade (like Turkey or Ukraine).

We conduct the clustering analysis on three different periods: (i) the starting period, May- June 2004 (period 1 in Table A1.1); (ii) the rating upgrade period, October-December 2006 (period 2 in Table A1.1); and (iii) the EU membership period, January-June 2007 (period 3 in Table A1.1). We also tested on other periods but the results were the same, so we did not include them.

Before applying the clustering method, the data are normalized. This ensures that the variables are positioned on the same scale. Then we apply the algorithm using various distance definitions and select the results with the highest consistency (i.e. with the maximum cophenetic correlation coefficient). For the k-means algorithm we also check that the solution is not a local minimum.

The main finding (details in Annex 1) is that a rating upgrade or an alteration in the EU membership status does not have a significant impact in the way the investors are assessing the risk for a specific country. The differences in distance between countries spreads are not large enough to split the sample based on these two criteria. However, there is a regional factor that seems to be important. In all periods the sub-cluster made of Romania, Bulgaria and Croatia is maintained.

For the second question (i.e. the link between macroeconomic characteristics and the way the spreads are clustered), we compare the clusters built from spreads analysis with the clusters born from the macroeconomic fundamentals analysis (Annex 2). The purpose is to check if there is any connection between the clusters based on the macroeconomic fundamentals and the clusters due to the sovereign spreads.

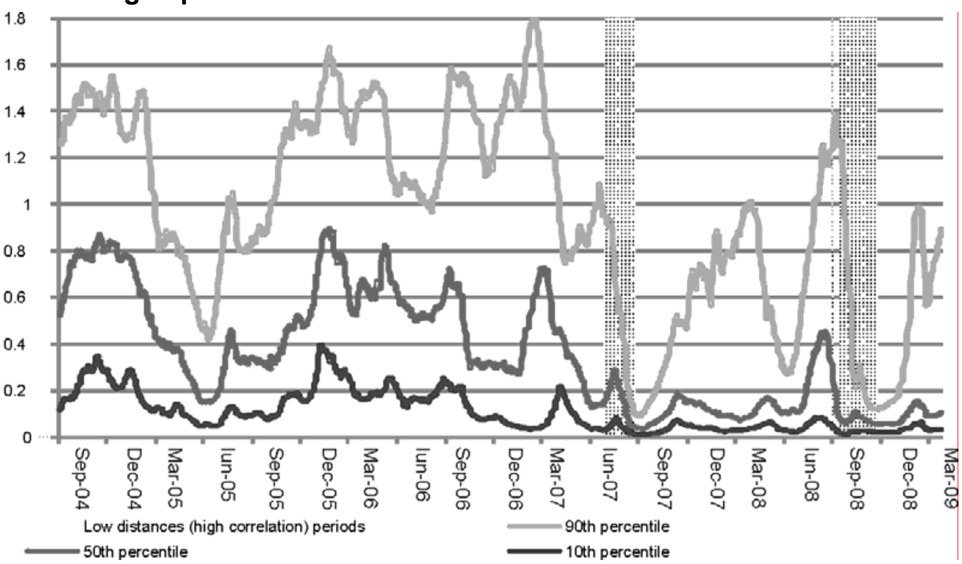
The analysis is very similar to that on spreads. We first normalize the data. Each country is represented in a high dimensional space (three to nine, based on the number of financial and macro economic variables used). The clustering algorithm is then applied to this data set. The variables are: GDP per capita, the ratio of current account to GDP, the annual inflation rate, the level of financial intermediation (expressed as private credit to M2 monetary aggregate), external debt to GDP, short-term external debt to GDP, reserves on short-term external debt, budget balance on GDP, and public debt on GDP.

The test was conducted for two periods: (i) 2001-2004, and (ii) 2005-2008. The test shows that Iceland has a clearly different pattern. The result is not clear for the other countries in the sample and there is no similarity between the results on spreads and those on fundamentals. Therefore, we cannot infer, based on the clustering technique, a clear link between fundamentals and spreads.

For the last question (if investors evaluate in different ways a country, depending on whether there are tranquil times or not), we check the distribution of distances between spreads, and how it changes in periods of high volatility. The narrower the distribution is (i.e., the lower the distances), the higher the correlation between spreads is (Figure 1). The periods with high correlations were determined based on the inter-percentile range. They correspond to August, 18 - October, 23, 2007 and October, 20, 2008 – January, 21, 2009.

Figure 1

Sovereign spreads distances based on correlation coefficient method

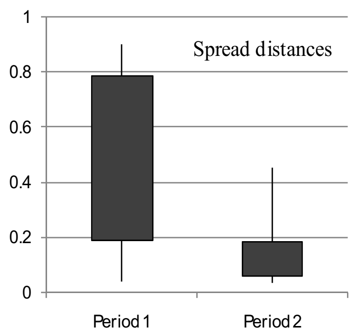


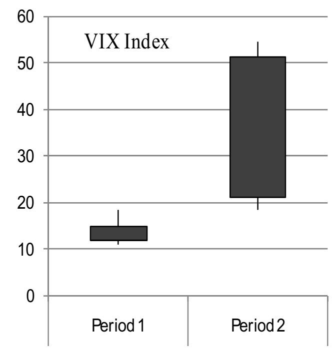
We find out that the spreads are more correlated since September 2007. The central moment of the spread distances' distribution shifted after this moment from 0.2-0.8 range to below 0.2 (with one exception – august 2008). The difference is statistically significant. The results are displayed in Table 1.

This last result is consistent with the result of the principal component analysis (Annex 3). The first principal component can be assumed to represent the market sentiment. It also can be shown that it is highly correlated with the VIX index. The results displayed in Table A3.1 explain more than 60% of data variance during the first period (during low volatility) and 95% after September 2007. Also, the loading factors (Table A3.2) point out that contributions for various countries are similar.

Table 1

t statistic and spread distances and VIX index distributions (bars based on 10-90 inter-percentile range, sticks min-max range)





t statistic for spread distances distributions	
Period 1*	0.47
Period 2**	0.10
t stat	40.52
confidence interval	(-Inf 0.34]

** 09/2004 – 08/2007*
*** 09/2007 – 03/2009*

4. Conclusions

Our main findings are: (i) during tranquil times, a rating upgrade does not deliver important adjustments in the way the investors are assessing the risk for a specific country; (ii) there is no clear connection between the clusters based on the macroeconomic fundamentals and the clusters due to the sovereign spreads; and (iii) the correlation increases in volatile times, the distances between spreads being significantly lower than in tranquil periods. Also, the market sentiment explains a much higher percentage of the spreads movements during turbulent times.

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Annex 1

The results of the cluster analysis on emerging European sovereign spreads[8]

Table A1.1. Cluster results for different periods and different rating changes

No	Period	Clusters (countries and avg. sprd.)	Rating/UE membership changes	No. of countries speculative grade
1	05/2004–07/2004	Cluster 1: CZ Cluster 2: all the others	no changes	5 (RO, BG, TR, RU, UA)
2	10/2006–12/2006	Cluster 1: CY,LT Cluster 2: all the others	10/6/2006 (Moody's) from Ba1 to Baa3 for Romania	2 (TR, UA)
3	01/2007–06/2007	Cluster 1: CZ Cluster 2: all the others	Romania and Bulgaria became UE members	2 (TR, UA)
4	10/2008 12/2008	Cluster 1: TR Cluster 2: all the others	10/27/2008 (S&P) and 11/10/2008 (Fitch) downgraded Romania to speculative risk class	3 (TR, UA, RO)

Chart A1.1 – Clusters[9] for 5/07/2004 - 7/30/2004
Cophenetic correlation test: 0,94

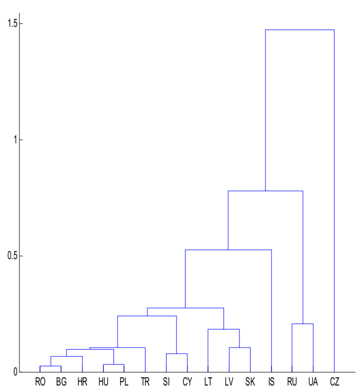
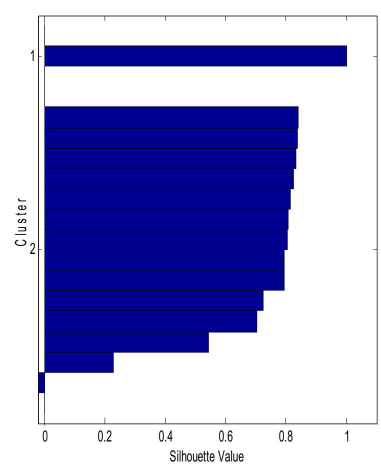


Chart A1.2 – Silhouette values for two clusters - mean: 0.70



[8] All the results presented in this section are calculated based on both hieratical and k-means methods. The results were identical most of the time. The methods used are determined by maximizing the two performance indicators presented in the paper: the cophenetic correlation and the silhouette test.

[9] The order on the horizontal axis has no meaning; the values on the vertical axis show the scale of the link between clusters.

Chart A1.3 – Clusters for period 10/2/2006 – 12/29/2006
Cophenetic correlation test: 0,84

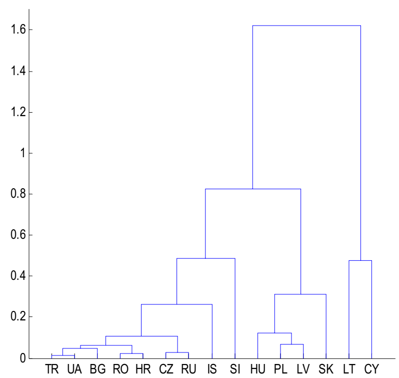


Chart A1.4 – Silhouette values for two clusters - mean: 0.68

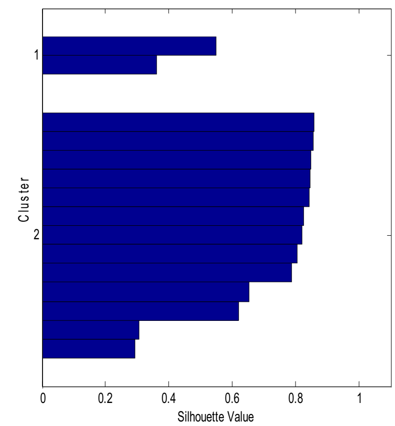


Chart A1.5 – Clusters for period 1/1/2007 – 6/29/2007
Cophenetic correlation test: 0,96

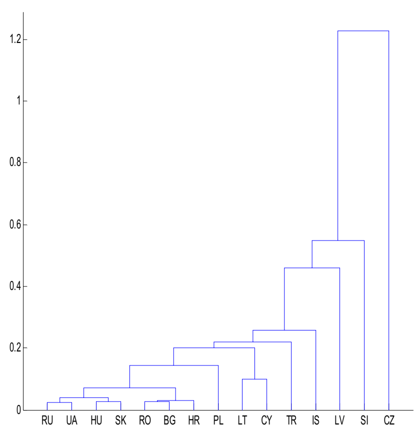


Chart A1.6 – Silhouette values for two clusters - mean: 0.78

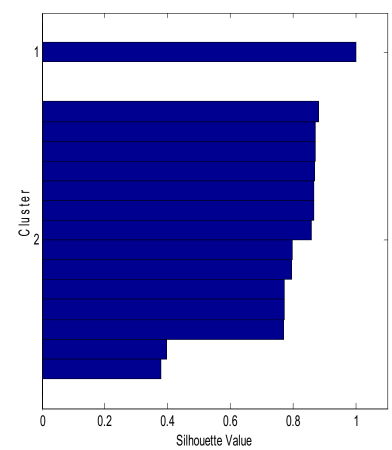


Chart A1.7 – Clusters for period 10/1/2008 – 12/31/2008
Cophenetic correlation test: 0,91

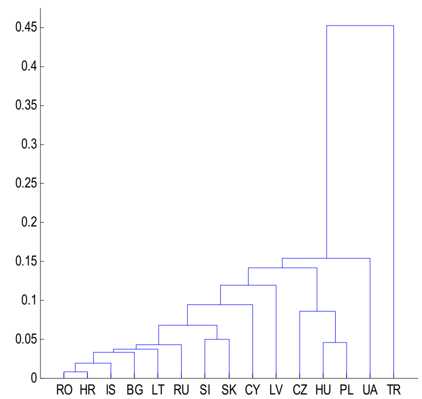
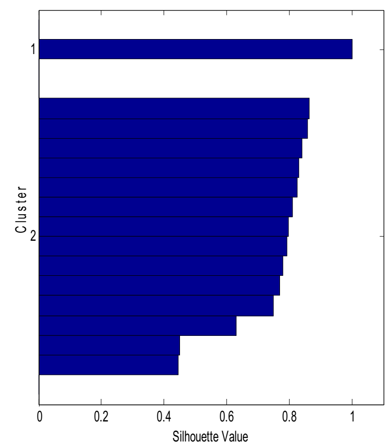


Chart A1.8 – Silhouette values for two clusters - mean: 0.76



Annex 2

The dendrograms for cluster analysis on macroeconomic indicators[10]

Chart A2.1. Clusters for 2001-2004

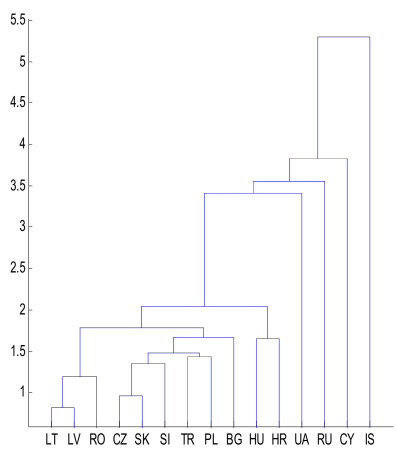
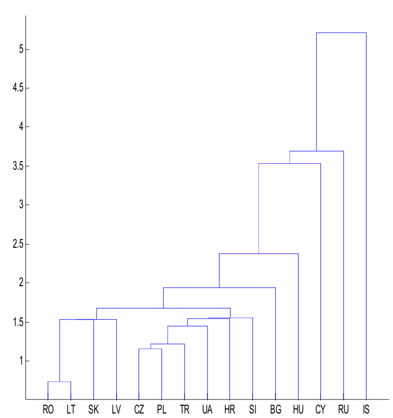


Chart A2.2. Clusters for 2005-2008[11]



[10] For Budget Balance/GDP and Public Debt/GDP the values are only for 2005 and, respectively, 2007.

Table A2.1 Macroeconomic characteristics of the clusters for 2001-2004

	Cluster 1	Cluster 2	Cluster 3
Countries	LV,LT,RO,SK,BG, CZ,TR,PD,UR,HR,SI,HU,RU	IS	CY
Cophenetic correlation: 0.91			
Silhouette test: 0,70			
GDP per capita (mil USD)	3,254	35,447	17,121
CA/GDP (%)	5.6	-4.3	-3.5
Inflation rate (%)	1.9	3.5	3.0
CNG/M2 (%)	20.8	569.7	134.1
External Debt/GDP (%)	11.7	87.2	91.3
ST External Debt/GDP (%)	3.6	29.6	45.0
Reserves/ST External Debt	1.6	0.2	0.6
Budget Balance/GDP (%)	3.7	4.9	-2.4
Public Debt/GDP (%)	15.0	25.4	69.1
Source: IMF, BIS, ECB, countries' Central Banks			

Table A2.2 Macroeconomic characteristics of the clusters for 2005-2008

	Cluster 1	Cluster 2
Countries	LV,LT,RO,SK,BG, CZ,TR,PD,UR,HR,SI,HU,RU, CY	IS
Cophenetic correlation: 0.93		
Silhouette test: 0,79		
GDP per capita (mil USD)	11,826	58,317
CA/GDP (%)	-6.9	-18.6
Inflation rate (%)	5.9	4.3
CNG/M2 (%)	102.4	959.8
External Debt/GDP (%)	55.8	276.1
ST External Debt/GDP (%)	22.3	134.1
Reserves/ST External Debt	1.7	0.1
Budget Balance/GDP (%)	-0.6	5.2
Public Debt/GDP (%)	31.2	28.6
Source: IMF, BIS, ECB, countries' Central Banks		

Annex 3

Principal Component Analysis

Table A3.1 – Explained variance

	Period 1*		Period 2**	
	Explained	Cumulative	Explained	Cumulative
Principal component 1 (PC1)	63.3	63.3	95.5	95.5
Principal component 2 (PC2)	13.9	77.2	2.7	98.2
Principal component 3 (PC3)	7.6	84.8	0.6	98.8
Principal component 4 (PC3)	6.8	91.6	0.4	99.2
Principal component 5 (PC3)	3.4	95.0	0.3	99.5
Principal component 6 (PC3)	1.6	96.6	0.2	99.7

Table A3.2 – Loading factors[12]

No	Period 1*						Period 2**	
	PC1	PC2	PC3	PC4	PC5	PC6	PC1	PC2
Czech Republic	-0.28	0.18	-0.07	0.23	0.08	**-0.65**	0.25	0.39
Romania	-0.29	0.03	-0.34	0.15	0.06	0.20	0.25	-0.39
Bulgaria	-0.30	-0.01	-0.32	0.09	0.02	0.13	0.26	-0.08
Hungary	-0.16	-0.27	0.19	-0.70	0.28	-0.12	0.26	-0.03
Turkey	-0.29	0.02	-0.35	0.07	0.02	-0.01	0.24	**-0.62**
Poland	-0.28	-0.09	-0.26	-0.15	0.39	-0.23	0.26	-0.12
Croatia	-0.26	-0.22	-0.24	-0.21	-0.21	**0.48**	0.26	-0.12
Lithuania	-0.21	-0.36	0.21	**0.43**	0.16	0.17	0.26	0.17
Slovenia	0.18	**-0.52**	-0.24	0.04	0.19	-0.23	0.26	0.02
Russia	-0.29	0.25	0.16	-0.13	-0.17	0.04	0.26	0.21
Ukraine	-0.28	0.23	0.14	-0.27	0.02	0.05	0.26	0.04
Latvia	-0.30	0.09	0.28	0.15	-0.04	-0.02	0.26	0.26
Cyprus	-0.20	-0.35	**0.46**	0.21	0.21	0.14	0.25	0.34
Iceland	-0.18	**-0.42**	0.02	-0.07	**-0.76**	-0.33	0.26	-0.12
Slovak Republic	-0.30	0.11	0.23	0.02	0.00	-0.08	0.26	0.01

** 09/2004 – 08/2007*
*** 09/2007 – 03/2009*

[12] All the weighs that in absolute terms are over 0.4 are showed in bold.

Annex 4

Statistics of bonds used in the analyses

Table A4.1 – Bonds

No	Country		ISDN	Credit Rating			Amount	Maturity	Spreads (avg., %)		
				Mar-04	Nov-07	Dec-08	mil. EUR	years	period 1	period 2	period 3
1	CZ	Czech Republic	CZ0001000814	6.3	5.7	5.3	2,448	4.5	22.7	10.8	37.54
2	RO	Romania	XS0147466501	12.7	9.7	10.7	700	3.4	27.0	37.7	74.46
3	BG	Bulgaria	XS0145624432	11.7	9.0	9.7	810	4.1	23.9	31.2	65.38
4	HU	Hungary	XS0161667315	6.3	7.3	8.3	1,000	4.1	10.4	24.6	66.84
5	TR	Turkey	DE0004516752	13.7	13.0	13.0	1,000	1.1	64.2	36.1	64.52
6	PL	Poland	XS0144238002	7.3	6.7	6.7	750	3.2	9.5	16.9	50.22
7	HR	Croatia	XS0126121507	10.0	9.7	9.7	750	2.2	14.9	32.4	66.12
8	LT	Lithuania	XS0147459803	7.3	6.0	7.0	1,000	3.4	7.2	21.1	65.42
9	SI	Slovenia	XS0127672938	4.3	3.0	3.0	450	2.3	1.5	11.0	33.56
10	RU	Russia	RU0001342198	11.0	8.3	8.3	1,194	2.4	83.8	20.2	49.54
11	UA	Ukraine	XS0170177306	14.3	13.3	14.3	682	4.5	101.7	77.5	89.99
12	LV	Latvia	XS0189713992	7.7	7.7	9.0	400	5.3	13.2	31.8	66.23
13	CY	Cyprus	XS0143546207	5.7	5.0	4.3	550	3.2	6.0	17.3	33.91
14	IC	Iceland	XS0145825179	3.3	3.7	9.3	250	3.3	8.4	20.4	65.00
15	SK	Slovak Republic	XS0192595873	7.7	5.7	5.0	1,000	5.4	13.3	15.2	46.00

Source: Bloomberg.

Table A4.2 – Codes applied to ratings class

S&P/Fitch	AAA	AA+	AA	AA-	A+	A	A-	BBB+	BBB	BBB-	BB+	BB	BB-	B+	B	B-
Moody's	Aaa	Aa1	Aa2	Aa3	A1	A2	A3	Baa1	Baa2	Baa3	Ba1	Ba2	Ba3	B1	B2	B3
Code	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16