THE BEHAVIOUR OF CENTRAL AND EAST EUROPEAN STOCK MARKETS DURING HIGH-VOLATILITY EPISODES

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Abstract

Our paper’s objective is to identify recurrent patterns in the behaviour of eleven Central and East European (CEE) stock markets that are members of the European Union during high volatility episodes in international financial markets, using cluster analysis. Our research is relevant from the perspective of the financial integration process in the European Union, as financially integrated markets should demonstrate similar behaviour, even in highly turbulent times. Using stock market return distributions from CEE countries between 1999 and 2014, we find thatCEE countries are rather heterogeneous in terms of skewness, but more homogeneous in terms of mean returns and excess kurtosis. Also, their return distributions’ properties change across high-volatility episodes and place them in different clusters from one episode to another, thus making forecasting these countries’ stock return an endeavour in turbulent times. At the same time, they can be successfully used as diversifiers in European portfolios in times of high-volatility, given their dissimilarity with EMU returns.

Key words:volatility, stock markets, cluster analysis, risk diversification, international investments

JEL Code:F21, G15

Introduction

High volatility episodes in international financial markets change the risky positions undertaken by traders and investors, thus hindering the benefits of international diversification. An understanding of stock markets similarities and differences during turbulent times is insightful for international portfolio investors, as such periods put under pressure the risk diversification process. At the same time, our results might prove to be interesting from the perspective of the financial integration process in the European Union; as evidenced by the existing literature, financially integrated markets should demonstrate similar behaviour, even in highly turbulent times.

Risk changes in the dynamics of stock returns is the objective of various seminal papers, whose overall purpose resided in identifying stylized facts regarding the regular dynamics of volatilities, such as volatility clustering, time dependence, asymmetries or spillover effects.Schwert (1989) set forth an early analysis regarding the connection between volatility of stock returns and volatilities for macroeconomic variables, using monthly data and noting that previous research highlighted the large volatility of equity prices during the Great Depression. Schwert (1990) continues the volatility investigation on the stock market behavior during the October 1987 crash; the stock market reaction in this period was so unexpected and the volatility returned to previous market levels so quickly that the understanding of the roots of the volatility spikes in stock market dynamics fed various following studies.

Many volatility models used in the analysis of stock price changes were created to capture the clustering effect which was evidenced as a sequence of episodes of low range dynamics followed by episodes of large changes. For example, Gaunersdorfer and Hommes (2007) attempt to monitor the sudden changes in volatility using regime shifting techniques and highlighting the fact that the clustering represents a feature that lies inside the market dynamics. In the same vein, Wang and Moore (2009) analyzed these shifts in volatility for the case of the stock markets inside the European Union in a period that covered the time interval before the crisis in 2007 but also regional stock market crashes with an international impact. They concluded that "sudden changes" in volatility arise as a consequence of special dynamics detected in the emerging markets, shifts in the exchange rate policy and the notorious stock market crashes that characterized this period.

From the international perspective of stock market volatility dynamics we mention the studies covering the importance of co-movement and propagation of shocks across countries. For instance, Edwards and Susmel (2001) investigate the correlation of high volatility episodes across countries by looking at the Latin American stock markets. They use regime shifting models and a gauge of the co-dependence of volatility regimes to find that the respective episodes are short-lived and manifest in the same time in the Mercosur countries.Under a similar track, Kaminsky and Reinhart (2002) enquire which are the markets that tend to be mostly synchronized and feature the largest co-movement at the international level for a small sample period covering 1997–1999 and 35 countries. They find interesting spillover effects by using analysis of market dynamics around peaks in interest rates and maximum negative changes in stock market returns.

Our work maintains this research quest aiming at analyzing the distributional properties of stock market returns during high volatility episodes in the dynamics of equity markets and comparing these features among various stock markets pairs to identify possible similar effects. At the same time, we continue the previous research on the behaviour of stock markets in the European Union undertaken by Horobet and Lupu (2009) and on the financial integration of European stock markets using multivariate data analysis undertaken by Horobet et al. (2014).

The paper continues with a presentation of the data and methodology employed in our analysis, a presentation of the main results and concludes with some remarks that cover our main findings.

1 Data and research methodology

We analyseeleven stock market indices from CEE countries that are currently members of the European Union - Bulgaria (SOFIX Index), Czech Republic (PX Index), Croatia (CROBEX Index), Estonia (TALSE Index), Hungary (BUX Index), Latvia (RIGSE Index), Lithuania (VILSE Index), Poland (WIG20 Index), Romania (BET Index), Slovakia (SAX Index) and Slovenia (SVSM Index until 13/10/2010 and SIBTOP Index afterwards). We use the stock market indices with daily frequency, for the period between January 4, 1999 and December 31, 2014. As a comparison referential, we also include in the analysis the DAX Index of the German stock markets, as a representative index for the EMU markets. Data on all 12 markets is collected from Bloomberg.

We identify high-volatility episodes based on daily values of VIX, an indicator widely-used as a proxy for global financial market volatility, collected from CBOE. We define the start of a high-volatility episode as the day when the VIX moves 10 percentage points above its 60-day backward-looking moving average. The end of a high volatility episode is defined as the day when VIX returns to a value which is below the threshold for the start of the high-volatility episode. Table 1 below shows the nine high-volatility episodes we identified, along with the number of currency returns observations for each of them, based on the methodology described above. The longest high-volatility episode is Episode 6 (52 observations), while the shortest one is Episode 9 (24 observations).

From here, our analysis is developed in two parts: (i) we study the first four moments of the stock markets returns frequency distributions (average, standard deviation, skewness, and kurtosis) for each high-volatility episode; (ii) based on distributions' properties, we apply cluster analysis to identify similarities and differences between the behaviour of European stock markets across all high volatility episodes.

Cluster analysis' goal resides in identifying natural clusters according to a specific internal criterion, without knowing a priori the affiliation of entities to the clusters, based on entities' similarities and differences between them. From our research perspective, the result of this analysis refers to finding homogeneous groups of stock markets depending on the featured attributes, i.e. returns distributions moments. We are interested in observing the particular position of countries in clusters for each high-volatility episode, depending on the first four moments of distributions returns - mean, standard deviation, skewness and kurtosis.

Tab. 1: High-volatility episodes, 1999-2014

No. of episode	Time interval	Number of observations
1	October 6, 2000 - November 16, 2000	30
2	August 30, 2008 - October 23, 2001	34
3	June 3, 2002 - August 13, 2002	51
4	May 12, 2006 - June 20, 2006	27
5	July 20, 2007 - August 23, 2007	25
6	September 12, 2008 - November 25, 2008	52
7	May 4, 2010 - June 14, 2010	29
8	July 26, 2011 - October 5, 2011	51
9	May 11, 2012 - June 14, 2012	24

Source: Authors' calculations

We apply the k-means clustering algorithm, which assigns entities to clusters so that the means across clusters for all variables included in the algorithm are as different as possible from each other (see Hartigan and Wong (1978), and Witten and Frank (2000)). The method we use is implemented in the Generalized EM and k-Means Cluster Analysis module of STATISTICA, which extends the traditional k-means approach in two ways: (i) this algorithm computes probabilities of cluster memberships based on one or more probability distributions, with the goal of maximizing the overall probability or likelihood of the data, given the final clusters; (ii) the module uses a modified v-fold cross-validation scheme to determine the best number of clusters from the existing data, thus overcoming the need to specify the number of clusters a priori.

2 Results

1.1 Analysis of stock markets returns

The first part of our research observes stock markets returns frequency distributions for all nine high-volatility episodes, with the aim of identifying preliminary behavioural patterns for each episodes. Tables 2 to 4 show the means of daily returns, the skewness and excess kurtosis for the twelve markets that we briefly overview. An analysis of the means confirms that stock markets generate average negative returns in times of financial turbulence - this is easily observable in Table 2 -, although some countries have not experienced negative mean returns in all high-volatility episodes. These positive means were recorded particularly in Episodes 1 to 3 and it should be noted that DAX also did not record negative mean returns in Episode 1. All CEE indices had negative mean returns in Episodes 4, 6, and 8, while Episode 1 recorded the highest number of countries with positive mean returns (6). The Czech Republic and Croatia are the only countries without positive mean returns across episodes, while Slovakia and Slovenia are the countries with the highest number of positive mean returns (3). The highest average mean return across all countries is recorded for Episode 1 (0.02%, lower than DAX returns of 0.03%), while the lowest average mean return is found for Episode 6 (-1.05%, with the DAX return at its lowest value across all episodes, -0.64%).

Tab. 2: Stock market returns means, all high-volatility episodes

	Mean_1	Mean_2	Mean_3	Mean_4	Mean_5	Mean_6	Mean_7	Mean_8	Mean_9
BG	n/a	n/a	0.0026	-0.0002	0.0017	-0.0188	-0.0026	-0.0044	-0.0023
CZ	-0.0026	-0.0002	-0.0005	-0.0052	-0.0024	-0.0088	-0.0029	-0.0054	-0.0016
CRO	n/a	n/a	-0.0022	-0.0010	-0.0004	-0.0126	-0.0029	-0.0035	-0.0039
EST	0.0016	-0.0012	-0.0027	-0.0034	-0.0041	-0.0125	-0.0025	-0.0052	-0.0013
HU	-0.0030	0.0006	-0.0029	-0.0099	-0.0045	-0.0095	-0.0034	-0.0054	-0.0011
LAT	0.0032	-0.0063	-0.0005	-0.0031	0.0001	-0.0083	-0.0012	-0.0026	-0.0020
LIT	0.0011	0.0000	0.0008	-0.0037	-0.0007	-0.0156	0.0000	-0.0042	-0.0012
PL	-0.0006	0.0012	-0.0048	-0.0085	-0.0032	-0.0066	-0.0007	-0.0047	0.0006
RO	0.0013	-0.0019	0.0006	-0.0039	-0.0024	-0.0099	-0.0044	-0.0048	-0.0049
SLO	0.0012	0.0003	-0.0007	-0.0004	0.0013	-0.0094	-0.0038	-0.0033	-0.0023
SVK	-0.0002	0.0019	0.0000	-0.0027	0.0014	-0.0039	-0.0015	-0.0010	-0.0004
GER	0.0003	-0.0024	-0.0050	-0.0027	-0.0020	-0.0060	0.0007	-0.0058	-0.0029

Source: Authors' calculations

The highest value of the standard deviation for returns is recorded in Episode 6 (0.0386) and the lowest value is recorded in Episode 9 (0.0105). Across all episodes and countries, the highest standard deviation of returns belongs to CZ in Episode 6 (0.0578), and the lowest to BG in Episode 4. It is interesting to note that the average standard deviation for the CEE markets was lower than the German market standard deviation in six out of the nine episodes (Episodes 1 to 4, 6 and 8). The average skewness of returns is positive in five episodes (1, 4, 6, 7 and 9) and negative in four episodes (2, 3, 5 and 8), with countries displaying either positive or negative skewness during the nine episodes. SVK and RO record positive skewness in 6 episodes each, followed by CRO and PL with 5 episodes with positive skewness. At the other end, BG recorded positive skewness in only one episode.

Tab. 3: Stock market returns skewness, all high-volatility episodes

	Skew_1	Skew_2	Skew_3	Skew_4	Skew_5	Skew_6	Skew_7	Skew_8	Skew_9
BG	n/a	n/a	-1.0546	-0.4191	-0.1107	-0.0601	-0.3063	-0.1839	0.3335
CZ	0.1839	-0.2890	-0.0684	0.4847	-0.9944	0.0264	0.3256	-0.2921	-0.0645
CRO	n/a	n/a	0.0722	0.4940	0.3628	0.8820	0.3081	-0.8877	-0.1520
EST	-0.3955	-0.1833	-0.9572	0.0119	-0.9241	0.1368	0.3295	-0.3154	0.0682
HU	-0.0672	-0.2915	-0.3888	0.3117	-0.1069	0.2624	1.4399	-0.1314	-0.3135
LAT	-0.4128	-0.7232	0.0685	-0.1583	-0.0744	0.5681	0.1363	-0.0999	0.6777
LIT	-0.4200	-0.1591	0.1794	0.5186	-0.6377	0.7823	0.5123	-0.0993	-0.4653
PL	0.3540	0.4307	0.3382	-0.3866	-0.1072	0.0051	0.5857	-0.5376	-0.1057
RO	-0.1595	0.6149	0.3703	0.1300	0.3209	0.2903	0.1535	-0.8374	-0.6859
SLO	1.0882	-2.2150	-0.0052	-0.1081	-0.7885	0.1243	-0.8019	-1.0803	0.3456
SVK	0.7337	0.5431	0.2414	-0.7500	0.5795	0.6849	-2.2820	-1.0999	0.8335
GER	0.8804	-0.6693	0.5294	-0.1604	-0.2324	0.8209	0.3395	0.1083	-0.5401

Source: Authors' calculations

CEE countries return distributions were, on average, leptokurtic in each episode, which represents a different behaviour compared to Germany (DAX had leptokurtic distributions in four episodes and platykurtic distributions in five episodes). The highest value of excess kurtosis is recorded by SVK in Episode 7 (9.0879) and the lowest is recorded by HU in Episode 4.

Tab. 4: Stock market returns excess kurtosis, all high-volatility episodes

	Kurt_1	Kurt_2	Kurt_3	Kurt_4	Kurt_5	Kurt_6	Kurt_7	Kurt_8	Kurt_9
BG	n/a	n/a	6.5607	1.2235	0.2328	-0.4393	1.2250	-0.0614	2.2076
CZ	0.0308	0.0346	-0.4896	0.9520	1.5884	0.5456	0.7276	0.0595	-0.7806
CRO	n/a	n/a	1.2104	1.4665	3.9014	2.5043	-0.7851	2.2339	-0.0051
EST	-0.6115	-0.1145	2.5832	1.4375	0.2878	-0.0994	-0.3793	0.6033	0.8406
HU	0.1940	0.5653	1.6253	-1.2851	-0.0482	0.8345	5.2764	0.7691	0.4666
LAT	0.7809	0.5020	-0.6628	0.6299	0.8729	0.7623	-0.1076	0.4543	1.0529
LIT	0.8628	0.4148	0.7520	1.2342	0.4114	2.4392	1.5090	1.8972	0.3868
PL	-0.5308	0.4309	-0.0654	-0.4644	1.5085	-0.3507	0.8982	0.4109	0.0274

RO	-0.8207	0.3803	0.1534	2.8138	-0.6355	0.1500	1.7665	3.4657	1.1584
SLO	0.7446	7.0885	-0.2019	1.4978	0.8500	0.2281	1.2453	3.3826	-0.3679
SVK	1.1523	1.2242	2.1122	0.4314	0.9047	7.3259	9.0879	3.7682	2.4139
GER	-0.2415	0.9498	-0.1612	-0.8938	-1.2343	1.2309	0.7076	-0.7271	0.6233

Source: Authors' calculations

1.2 K-means cluster analysis

The results of our cluster analysis are summarized in Table 5 and Figure 1 below. Table 1 shows countries' placements in clusters for each high-volatility episode and the distance of each country from the centroid, based on the four moments of returns' distributions. By far, the most heterogeneous episodes are 6 and 7, when six and five clusters, respectively, are formed. At the other end, episodes 1, 5, 8 and 9 are the most homogeneous ones, with only two clusters formed.

Tab. 5: Cluster membership and distance to centroid, all high-volatility episodes

	Episode 1		Episode 2		Episode 3		Episode 4		Episode 5		Episode 6		Episode 7		Episode 8		Episode 9	
	Cluster	DC	Cluster	DC	Cluster	DC	Cluster	DC	Cluster	DC	Cluster	DC	Cluster	DC	Cluster	DC	Cluster	DC
BG	n/a	n/a	n/a	n/a	1	0.0000	1	0.3208	1	0.2722	1	0.0000	3	0.1281	1	0.2518	1	0.3053
CZ	1	0.3969	1	0.1570	3	0.3067	2	0.5111	2	0.5141	2	0.0000	2	0.2727	2	0.1284	2	0.4252
CRO	n/a	n/a	n/a	n/a	3	0.2113	3	0.3637	1	0.6287	3	0.1481	3	0.1658	3	0.2618	2	0.4633
EST	2	0.3459	1	0.2078	3	0.6662	3	0.2490	2	0.5481	4	0.1303	3	0.2416	2	0.2350	1	0.3719
HU	1	0.5292	1	0.1545	3	0.4508	2	0.3567	2	0.2822	5	0.1826	5	0.0000	2	0.1607	2	0.3023
LAT	2	0.4722	2	0.3428	3	0.2208	1	0.2188	1	0.1066	6	0.3677	4	0.2063	1	0.2372	1	0.2651
LIT	2	0.4307	1	0.1145	3	0.3622	3	0.2469	1	0.4342	3	0.1481	4	0.1695	1	0.2916	2	0.5878
PL	1	0.6790	1	0.2306	2	0.3224	2	0.4310	2	0.3516	5	0.2925	4	0.1279	2	0.2929	2	0.5876
RO	2	0.4939	1	0.3053	3	0.3464	3	0.3871	2	0.5647	5	0.1400	2	0.2727	3	0.5265	2	0.7229
SLO	1	0.7189	3	0.0000	3	0.1825	1	0.3167	1	0.4587	4	0.1303	3	0.2821	3	0.1017	2	0.5065
SVK	1	0.5013	1	0.3058	3	0.2907	1	0.3527	1	0.5617	6	0.6582	1	0.0000	3	0.5610	1	0.4543
GER	1	0.3795	2	0.3428	2	0.3224	1	0.5048	2	0.4018	6	0.3873	4	0.2060	2	0.4208	2	0.2716

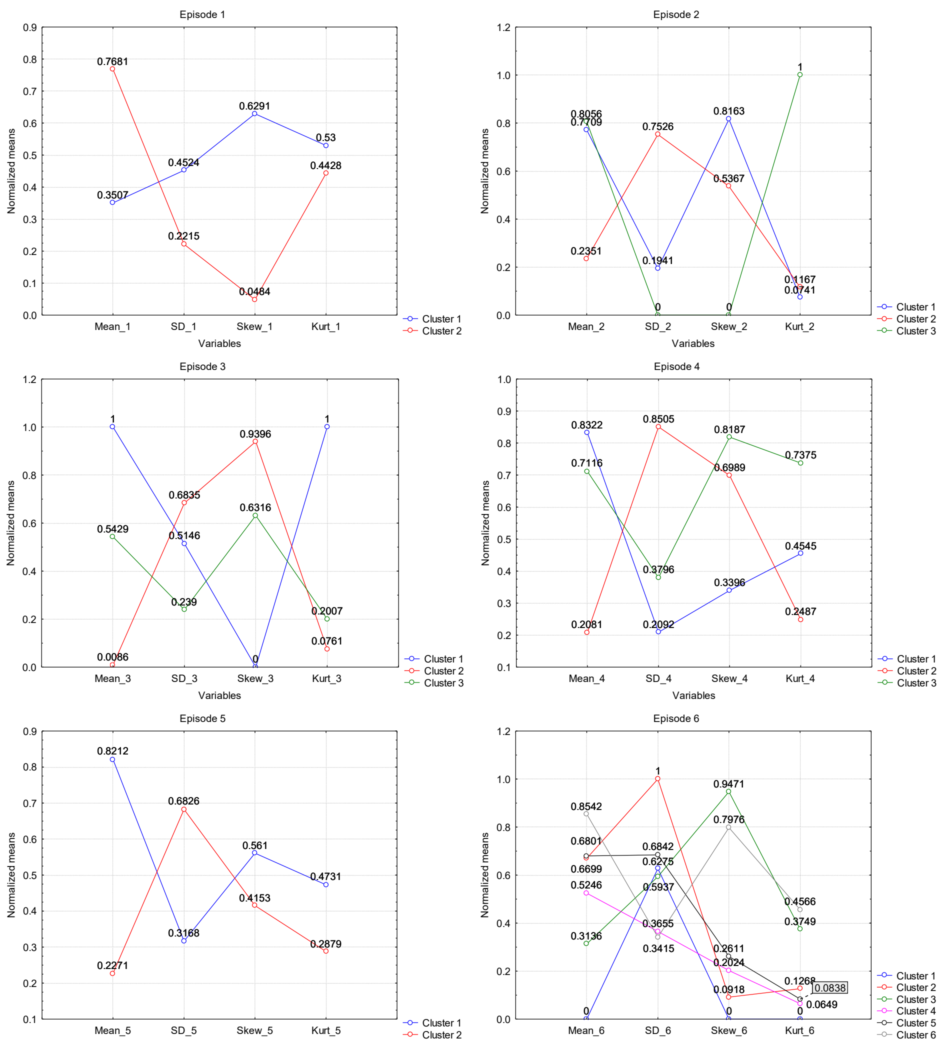
Note: (i) DC - Distance to centroid; (ii) n/a - not available, due to missing data for Episodes 1 and 2

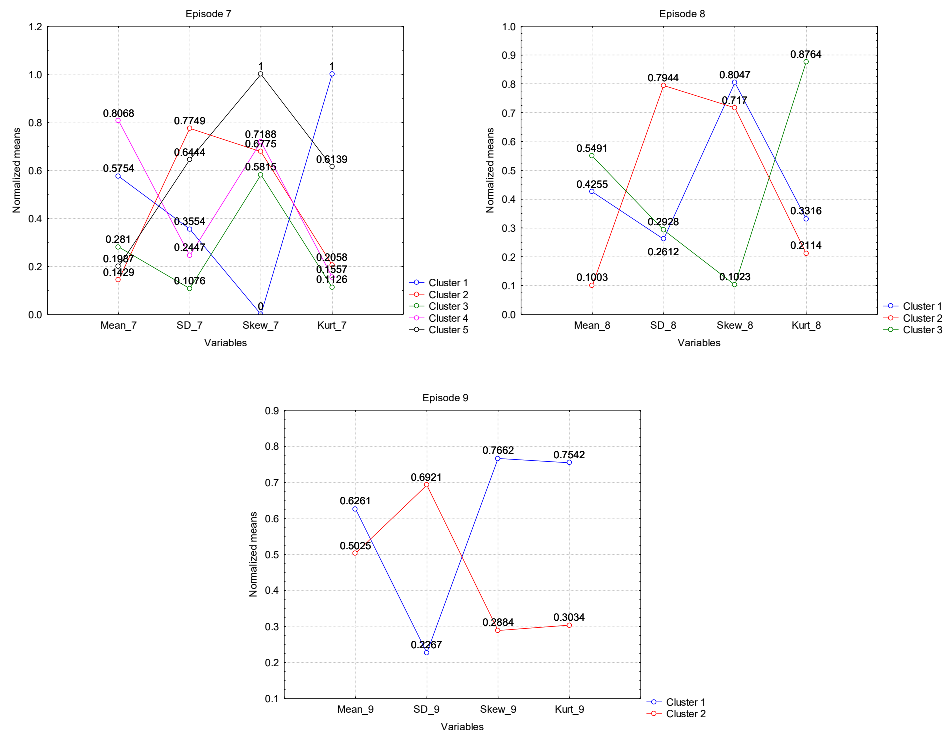
Source: Authors' calculations

Figure 1 presents the means of variables for the clusters in each episode, thus allowing us to observe differences between them. For some episodes the differences between clusters are clear (for example, in Episode 1, cluster 2 has a higher mean, but lower standard deviation, skewness and excess kurtosis than cluster 1; in Episode 9 the difference between clusters seems to be made mainly by standard deviation), but for some episodes the differences between clusters are smaller, which makes it difficult to identify only one variable that determines the clustering.

Countries' placements in clusters change across episodes, but a few observations are noteworthy: (i) Except for Episode 7, CZ and HU always belong to the same cluster; (ii) Baltic countries are clustered together in all episodes, but in most cases in pairs of two countries; (iii) in each episode, the composition of the DAX cluster changes, with no CEE country maintaining its position in the same cluster as DAX across all episodes.

Fig. 1: Clusters' means for variables - all high-volatility episodes





Source: Authors' calculations

Conclusion

Our research aimed at identifying recurrent patterns in the behaviour of eleven CEE stock markets during high volatility episodes in international financial markets, using a k-means clustering algorithm based on returns distributions properties. The analysis of return distributions first four moments revealed that countries in the region seem to be rather heterogeneous in terms of skewness, but more homogeneous in terms of mean returns and kurtosis.

Theclustering algorithm applied revealed that countries' stock markets are heterogeneous, with attributes that change across episodes and consequently place them in different clusters from one episode to another. This makes one think that forecasting these countries' stock return is a quite difficult endeavour, at least when financial turbulences are ahead. On the other hand, they can be successfully used as diversifiers in European portfolios in times of high-volatility, given their dissimilarity with EMU returns.

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