STYLIZED FACTS OF THE DAILY AND MONTHLY RETURNS FOR THE EUROPEAN STOCK INDICES DURING 2007-2012

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Abstract: *This study is intended to investigate the connection between the complexity of a capital market and the occurrence of dramatic decreases in transaction prices. The work hypothesis is that such episodes, characterized by sudden and dramatic decreases in transaction prices mostly occur in period of market inefficiency, when the level of complexity reaches a local minimum. In this regard, we introduce a complexity estimator, through differential entropy. The connection between the market complexity level and the appearance of extreme returns is illustrated in a logistic regression model.*

Key words: *differential entropy; stock market crash; logistic regression*

1. INTRODUCTION

This paper is dedicated to the study of the particularities in daily and monthly stock index returns for European markets during April 2007 and March 2012. Our comparative approach is based on three different dimensions. First we try to identify if the statistical behavior of the stock indices` returns is different between mature, emerging and frontier markets. Second, we look for particularities of monthly returns that are different from ones of the daily returns. Third, we document the specific behavior of the European stock indices` returns during the 2007-2009 stock market crisis in comparison with the evolution of the same indices after the March 2009 mid-term stock market bottom.

Over time, many investment managers and researchers studied the statistical characteristics of various stock market indices. Also, from obvious practical reason, the reactions of the stock markets on many types of previous financial and economic crisis were examined in detail by the research and academic community. More recently, starting with 2008, many authors showed interest to study the behavior of stock market returns during the 2007-2009 financial crisis.

Especially for investment managers, knowing the statistical characteristics of assets returns (such as mean, variance, skewness, kurtosis, the form of the distribution, the evolution in time of the correlation coefficients, the presence of autocorrelation in returns and squared returns etc.) represents an important step forward towards creating optimal portfolios.

During the last 30 years, the investment community was in particular interested by the less developed markets around the world, in search of larger profits and better portfolio diversification. Our study offers many useful details regarding the statistical behavior of stock market returns in particular for the emerging and frontier markets from Europe, during the recent, very difficult but also very relevant, period of time.

To cast some light on these issues, the rest of the paper is organized as follows: section 2 presents the most relevant Romanian and international related studies; section 3 describes the data that we worked with and the methodology that we have used; section 4 presents the results that we have obtained; finally section 5 summarizes the most important conclusions and proposes further studies in this field.

2. LITERATURE REVIEW

In 1998 Bekaert G., Erb C. B., Harvey C.R. and Vyskanta T.E. identify some clear differences of yield evolution in emerging markets: volatility high, low intensity correlation with mature markets and between emerging markets with each other, long-term high yields, greater predictability than can be achieved in mature markets, more likely to be influenced by external shocks (legislative, policy or exchange rate) [2].

Also, Bekaert G. and Harvey C.R. (1997) analyze the reasons that volatility is different across emerging markets, particularly with respect to the timing of capital market reforms. They argue that capital market liberalizations often increase the correlation between local market returns and the world market, but do not drive up local market volatility [1].

In 2001 Cont R. shows several features of logarithmic returns for a sufficient number of financial assets to believe that they have the character of generality. Account features specified refers to the absence autocorrelations in returns, high probabilities for extreme events (or thick tails of the distribution – "heavy tails"), asymmetry, higher values for standard deviation in comparison with the mathematical simple average, positive autocorrelation in squared returns and variance, leverage, correlation dependence time etc. [5].

Gelos R.G. and Sahay R. (2001) examined financial market co-movements across European transition economies and compared their experience to that of other regions. They found that correlations in monthly indices of exchange market pressures can partly be explained by direct trade linkages, but not by measures of other fundamentals [7].

Forbes K.J. and Rigobon R. (2002) argue that there is a high level of market co-movement during all periods, which he calls "interdependence". Previous research suggested that contagion (defined as a significant increase in market co-movement after a shock to one country) it is often occurring during crises. Forbes and Rigobon's paper is in opposition with that belief and shows that there was virtually no increase in unconditional correlation coeficients (i.e., no contagion) during the 1997 Asia crisis, 1994 Mexican devaluation and 1987 U.S. market crash [6].

Maroney N., Naka A. and Wansi T. explored risk and return relations in six Asian equity markets affected by the 1997 Asian financial crisis and found that after the start of the crisis, national equity betas increased (due to leverage linked to exchange rates) and average returns fell substantially. Subsequently, the authors propose a new probability-based asset pricing model that captures leverage effects using valuation ratios. Their results show the role of leverage in explaining the likelihood of the financial crises [10].

Hartmann P., Straetmans S. and de Vries C.G. (2004) characterize asset return linkages during periods of stress by an extreme dependence measure. Their estimates for the G-5 countries suggest that simultaneous crashes between stock markets are much more likely than between bond markets. Also, their data show that stock-bond contagion is approximately as frequent as flight to quality from stocks into bonds. Also, they found that extreme cross-border linkages are surprisingly similar to national linkages, illustrating a potential downside to international financial integration [9].

Latter, Bekaert G., Harvey C.R. and Ng A. (2005) studies contagion and propose a two-factor model with time-varying betas that accommodates various degrees of market integration. The authors apply this model to stock returns in three different regions: Europe, Southeast Asia, and Latin America. In addition to examining contagion during crisis periods, they document time variation in world and regional market integration and measure the proportion of volatility driven by global, regional, and local factors [2].

Pop C., Curutiu C. and Dumbrava P. (2009) present the Bucharest Stock Exchange evolution before the 2007-2009 crisis started to manifest and try to identify the main factors which influenced its explosive growth. The paper investigates the current financial crisis influences on Bucharest Stock Exchange – with an emphasis over the factors which might have deepen the descendent trend for the Romanian stock exchange market. The authors also present the effects of the current financial crisis on the future development of Bucharest Stock Exchange, taking into consideration the position of the Romanian capital market in Eastern Europe [12].

Harrison B., Lupu R., and Lupu I. (2010) studied the statistical properties of the CEE stock market dynamics using a panel data analysis and found that there is evidence of stationarity for the returns provided by the Romanian stock indices. They have also identified some particular characteristics of returns in these markets such as a great amount of non-linearity and cross correlation [8].

3. DATA AND METHODOLOGY

In our study we used the non-tradable stock market indices computed by the international financial advisory company MSCI Barra. The time series of daily and monthly prices for all the MSCI Barra indices are freely available at the company`s website www.msci.com and we were able to collect such daily and monthly data for the period April 2007 – March 2012.

For our research purpose we have selected 16 European stock markets, 2 international markets and 3 global stock market indices (needed in order to be able to make comparisons of the results). All those 21 indices were grouped in three categories: 6 developed market indices, 6 emerging market indices and 6 frontier market indices.

Because the price time series are not stationary, we preferred to transform all the 21 price time series into returns time series.

Regarding the returns estimation, as Strong (1992, p.353) pointed out "there are both theoretical and empirical reasons for preferring logarithmic returns. Theoretically, logarithmic returns are analytically more tractable when linking together sub-period returns to form returns over long intervals. Empirically, logarithmic returns are more likely to be normally distributed and so conform to the assumptions of the standard statistical techniques."[13]. This is why we decided to use logarithmic returns in our study since one of our objectives was to test of whether the daily returns were normally distributed or, instead, showed signs of asymmetry (skewness). The computation formula of the daily returns is as follows:

$$R_{i,t} = Ln\left(\frac{P_{i,t}}{P_{i,t-1}}\right) \quad (1)$$

where $R_{i,t}$ is the return of asset *i* in period *t*; $P_{i,t}$ is the price of asset *i* in period *t* and $P_{i,t-1}$ is the price of asset *i* in period *t-1*. As already mentioned above, according to this methodology of computing the returns, the prices of the assets must be adjusted for corporate events such as dividends, splits, consolidations and share capital increases (mainly in case of individual stocks because indices are already adjusted).

As a result of this initial data gathering we obtained 21 time series of log-returns, each with 1295 daily observations and 60 monthly observations.

For those 21 time series and two return frequencies we have computed the mean, standard deviation, skewness and kurtosis and also we have applied the Jarque Bera test of the normality of distribution of the daily returns.

For a financial time series the mean represents the simple mathematical average of all the observations within the sample. It is obtained by adding up the series and dividing the result by the number of observations.

The standard deviation of a financial time series is a measure of dispersion or spread in the series. The standard deviation is computed by:

$$\sigma = \sqrt{\frac{\sum_{i=1}^{N}(R_i - \bar{R})^2}{N-1}} \quad (2)$$

Where N is the sample size, R_i represents the individual observations of daily returns, and $\bar{R}$ represents the sample mean computed as above.

Concerning the estimation of skewness, according to most authors a time series of financial asset returns is symmetric around it's mean (noted here with μ) if:

$$\forall k, f(\mu + k) = f(\mu - k) \quad (3)$$

where f is the density function of the returns. If this property is valid then the mean of the returns series coincides with its median.

The skewness of a data population is defined as the third central moment. To be more precise, skewness is computed as the average cubic deviation of the individual observations from the sample mean, divided by the standard deviation raised to the third power. As a consequence of these considerations, we have calculated the sample skewness as follows:

$$\hat{S} = \frac{\frac{1}{N}\sum_{i=1}^{N}(R_i - \bar{R})^3}{\hat{\sigma}^3} \quad (4)$$

where $\hat{S}$ is the sample skewness; N is the total number of individual observations within the sample, R_i is the return of period t, $\bar{R}$ is the sample arithmetic mean and $\hat{\sigma}$ is an estimator for the standard deviation that is based on the biased estimator for variance ($\hat{\sigma} = \sigma\sqrt{(N-1)/N}$)

The skewness of a symmetric distribution, such as the normal distribution, is zero. Positive skewness means that the distribution has a long right tail and negative skewness implies that the distribution has a long left tail.

According to Peiro (1999), under normality hypothesis, the asymptotic distribution of $\hat{S}$ is given by $\hat{S} \rightarrow N(0, \frac{6}{T})$.

Kurtosis is a measure of how outlier-prone a distribution is. The kurtosis of the normal distribution is 3. Distributions that are more outlier-prone than the normal distribution have kurtosis greater than 3; distributions that are less outlier-prone have kurtosis less than 3 [11].

The kurtosis of a distribution is defined as

$$K = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{R_i - \bar{R}}{\hat{\sigma}}\right)^4 \quad (5)$$

where $\bar{R}$ is the mean of R_i, $\hat{\sigma}$ is the standard deviation of R_i, and N is the sample size. The kurtosis of the normal distribution is 3. If the kurtosis exceeds 3, the distribution is peaked (leptokurtic) relative to the normal. If the kurtosis is less than 3, the distribution is flat (platykurtic) relative to the normal.

The Jarque-Bera test is a two-sided goodness-of-fit test suitable when a fully-specified null distribution is unknown and its parameters must be estimated. The test statistic is

$$JB = \frac{N}{6}\left(s^2 + \frac{(k-3)^2}{4}\right) \quad (6)$$

where N is the sample size, s is the sample skewness, and k is the sample kurtosis. For large sample sizes, the test statistic has a chi-square distribution with two degrees of freedom. The reported probability (p-value) is the probability that a Jarque Bera statistic exceeds (in absolute value) the observed value under the null hypothesis. A small probability value leads to the rejection of the null hypothesis of a normal distribution.

4. RESULTS AND INTERPRETATIONS

The first step in investigating the properties statistical represents the calculation of the averages, variances, the asymmetry coefficients and the flattening coefficient, according to the methods described in the methodology section. The results obtained for the daily series of returns are presented in the table below. The specific parts for the monthly data will be will be discussed in the second part of this study.

Based on the table below we can already confirm that, for all the European stock markets included in this study, even though we speak about mature markets, emerging or frontier markets, even though the study is done on general indexes or on individual markets, the average of the long-term daily returns tends to zero. Also, included for all the markets in this study, we confirm that the average is statistically significantly close to the value of the median. Apart from observing the effective values from Table 1, these statements have been confirmed also by running the t-statistic test for the hypothesis of an average equal to 0 and respectively by the Sign, Wilcoxon and Van der Wareden tests for the hypothesis of a median equal to 0 in the case of all the 21 assets.

Table 1. Descriptive statistics for the series of daily returns

		Medie	Mediană	Maxim	Minim	Std. Dev.	Skew-ness	Kurtosis	Jarque-Bera	p-v.
Mature markets	Austria	-0.0010	0.0000	0.1277	-0.1119	0.0225	-0.026	6.951	841.994	0
	Franta	-0.0004	0.0000	0.1036	-0.0932	0.0174	0.099	7.899	1,296.085	0
	Germania	-0.0002	0.0000	0.1113	-0.0739	0.0169	0.130	8.245	1,486.650	0
	Italia	-0.0008	0.0000	0.1100	-0.0864	0.0184	0.043	7.269	982.833	0
	UK	-0.0003	0.0004	0.0950	-0.0938	0.0164	-0.106	8.711	1,761.008	0
	SUA	0.0000	0.0007	0.1044	-0.0915	0.0165	-0.151	9.026	1,962.978	0
	DM_Index	-0.0001	0.0007	0.0850	-0.0696	0.0124	-0.220	8.684	1,752.461	0
EM	China	0.0001	0.0002	0.1404	-0.1171	0.0224	0.171	7.665	1,179.811	0
	Cehia	-0.0002	0.0004	0.1675	-0.1568	0.0192	-0.287	16.662	10,081.670	0
	Ungaria	-0.0006	-0.0002	0.1733	-0.1999	0.0270	-0.028	9.208	2,077.982	0
	Polonia	-0.0004	0.0000	0.1125	-0.1124	0.0222	-0.223	6.335	610.344	0
	Rusia	-0.0002	0.0007	0.2376	-0.2334	0.0274	-0.294	18.032	12,201.200	0
	Turcia	0.0000	0.0002	0.1484	-0.1243	0.0246	-0.065	6.736	753.310	0
	EM_Index	0.0001	0.0006	0.1008	-0.0848	0.0151	-0.123	9.051	1,977.405	0
Frontier markets	Bulgaria	-0.0015	0.0000	0.1105	-0.1605	0.0193	-1.456	15.560	8,962.712	0
	Croatia	-0.0005	-0.0002	0.0998	-0.0803	0.0130	-0.199	13.701	6,182.963	0
	Estonia	-0.0005	0.0000	0.1241	-0.0924	0.0192	0.244	7.264	992.929	0
	Romania	-0.0007	0.0000	0.1043	-0.3358	0.0242	-2.179	32.879	49,158.980	0
	Slovenia	-0.0007	0.0000	0.0915	-0.0883	0.0139	-0.404	11.285	3,735.895	0
	Serbia	-0.0013	-0.0008	0.1502	-0.1725	0.0247	-0.352	11.196	2,847.822	0
	FM_Index	-0.0004	0.0004	0.0458	-0.0688	0.0104	-1.187	9.449	2,546.213	0

Source: MSCI Barra, calculations made by the authors

The results of the Sign, Wilcoxon and Van der Wareden tests from above are presented in Table 2 and show that we can not reject the null hypothesis (the mean = 0 and that median = 0) at the maximum permissible error level of 1% for none of the markets included in the study.

In this situation, were we can not affirm that for all the investigated assets, the average and the median for the daily returns does not differ significantly from zero, we can also statistically test if the affirmation that states that the averages and the medians for all the 21 temporal series with daily frequency are equal.

In order to test the equality of the medians we used the F test (ANOVA version and the Wech version), and for equal medians we used Chi squared tests, Kruskal-Wallis and Van der Waerden as seen in Table 3. The results for these tests are presented below in table 3 and show indeed that we have additional statistical arguments to state that medians and averages of the series for daily returns in all 21 studied assets are equal and have the value zero.

Table 2. The results for the statistic tests for the null hypothesis for the average=0 and the median=0 for the of daily returns series

		average=0	median=0			
		t-statistic	Sign (exact binomial)	Sign (normal approx.)	Wilcoxon signed rank	van der Waerden (normal scores)
		p-value	p-value	p-value	p-value	p-value
Mature markets	Austria	0.1297	0.627	0.627	0.385	0.2314
	Franta	0.3651	0.9328	0.9328	0.7036	0.4759
	Germania	0.5985	0.4139	0.4139	0.8543	0.8581
	Italia	0.1075	0.9775	0.9775	0.3759	0.1942
	UK	0.5696	0.1688	0.1688	0.8069	0.8561
	SUA	0.9677	0.0231	0.0231	0.2718	0.5542
	DM_Index	0.6927	0.0241	0.0241	0.2735	0.7173
Emergent markets	China	0.8406	0.4512	0.4512	0.7187	0.8293
	Cehia	0.7092	0.3873	0.3873	0.724	0.9393
	Ungaria	0.4278	0.6551	0.6551	0.4414	0.4013
	Polonia	0.4777	0.8011	0.8011	0.9433	0.7087
	Rusia	0.7712	0.3156	0.3156	0.4561	0.7295
	Turcia	0.9551	0.7174	0.7174	0.7222	0.8872
	EM_Index	0.8556	0.0846	0.0847	0.2327	0.4815
Frontier markets	Bulgaria	0.0146	0.1298	0.1298	0.0373	0.0253
	Croatia	0.1527	0.0547	0.0547	0.2115	0.2062
	Estonia	0.3382	0.0652	0.0652	0.1077	0.1431
	Romania	0.3247	0.9554	0.9554	0.7718	0.6253
	Slovenia	0.055	0.1528	0.1528	0.0611	0.0632
	Serbia	0.0925	0.0184	0.0184	0.0106	0.0235
	FM_Index	0.1632	0.1259	0.126	0.5437	0.8401

Source: MSCI Barra, calculations made by the authors

Returning to the other statistical characteristics of daily returns on stock markets, all from Table 1 we observe that for all the 21investigated assets, the standard deviation is higher than the value of the average (which we saw above that we can approximate to zero). This study confirms similar findings of previous research.

Interestingly, the results presented in Table 1 show us that we do not have enough statistical arguments clear to affirm that volatility (risk), measured by standard deviation (and implicitly of the variance) is higher for emerging stock markets. Although, as you can observe, standard deviation values for most of the six mature stock markets included in the study present lower figures compared with those of emerging and frontier markets, however the standard deviation for the daily returns in Austria is 0.0225 which exceeds the values for most emerging and frontier markets. This unusual situation is maintained also when we analyze the global indices.

The statistics presented in Table 1 show that for all the 21 assets studied, the kurtosis value (coefficient of vaulting) is higher than 3 (the specific value of normal distribution). This situation shows that the distributions of stock's daily returns are mostly leptokurtic, sharper than the normal distribution, with many values concentrated around the average values and thicker tails means high probability for extreme values (i.e. higher risks). Within the sample that contained mature markets, the kurtosis value does not exceed 10, showing the lowest levels. The highest levels of kurtosis are found for the frontier stock markets, which according to the figures from above signify a higher risk of investments in undeveloped markets compared to mature markets, findings that confirm results of previous similar studies.

Table 3. The results of statistical tests for the equality of averages and medians for the series of daily returns

	Anova F-test p-value	Welch F-test p-value
Null hypothesis: "all averages are equal"	0.924	0.907

	Med. Chi-squared	Kruskal-Wallis	van der Waerden
Null hypothesis: "all medians are equal"	0.000	0.267	0.617

Source: MSCI Barra, calculations made by the authors

Taking into account that the period analyzed in this study includes both a crisis cycle on the stock markets (with large and persistent declines in the period starting from June 2007 until February 2009) and an accelerated growth phase (between March 2009 - April 2012), offers us interest to study the behavior of standard deviation and maximum amplitude of variation for the two different stages. The result of this investigation is shown below in Table 4. and indicates that for all the 21 assets, the maximum variation amplitude during a trading session was lower during the upward trend compared to the crisis period.
At same the time we observe that for all 21 assets, their corresponding standard deviations had lower values during the upward trend compared with the values during the crisis.

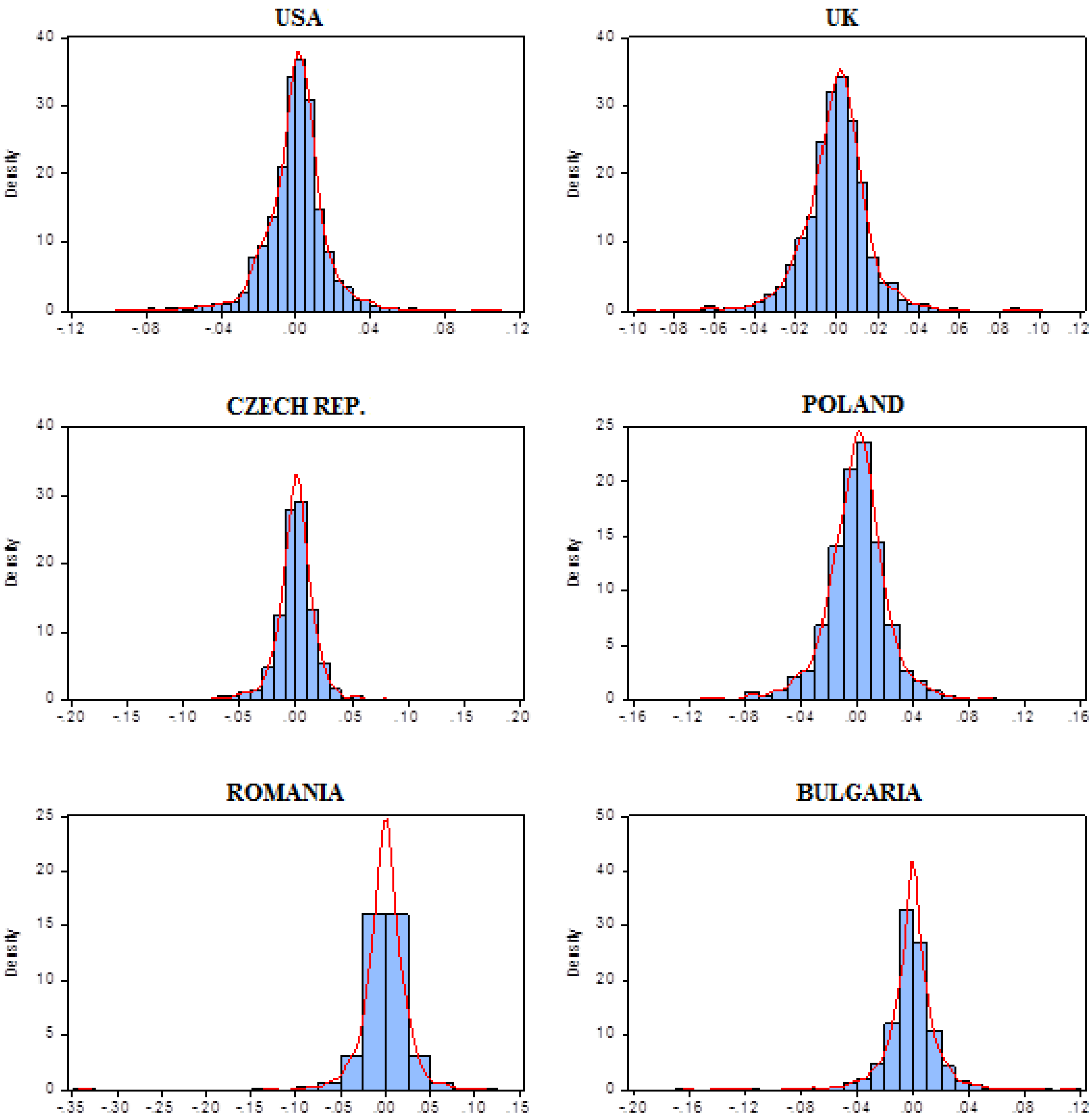

Figure 1 Comparison between actual probability distributions and the normal distribution of series of daily returns
Source: MSCI Barra, calculations made by the authors

Therefore this study confirms previous research findings, according to which the volatility of daily returns is amplified during downturns. The behavior characteristic of the daily stock returns is easily visible in Figure 3. Likewise, we observe that periods of high variance correspond to periods of high amplitude for daily returns.

Table 4. The evolution of volatility and business cycle asymmetry on the types of stock markets

		Standard period		Only the crisis			Only the upward trend		
		Std. Dev.	Skewness	Ampl. max	Std. Dev.	Skewness	Ampl. max	Std. Dev.	Skewness
Mature markets	Austria	0.0225	-0.026	0.1277	0.0269	0.098	0.0962	0.0195	-0.037
	Franta	0.0174	0.099	0.1036	0.0203	0.231	0.0883	0.0154	0.018
	Germania	0.0169	0.130	0.1113	0.0193	0.450	0.0601	0.0152	-0.161
	Italia	0.0184	0.043	0.1100	0.0193	0.411	0.1043	0.0179	-0.207
	UK	0.0164	-0.106	0.0950	0.0211	0.048	0.0642	0.0128	-0.146
	SUA	0.0165	-0.151	0.1044	0.0218	0.000	0.0693	0.0124	-0.188
	DM_INDEX	0.0124	-0.220	0.0850	0.0158	-0.029	0.0522	0.0097	-0.270
Emergent markets	China	0.0224	0.171	0.1404	0.0301	0.221	0.0648	0.0163	0.086
	Cehia	0.0192	-0.287	0.1675	0.0254	-0.257	0.0731	0.0144	0.018
	Ungaria	0.0270	-0.028	0.1999	0.0303	-0.146	0.1478	0.0249	0.172
	Polonia	0.0222	-0.223	0.1125	0.0251	-0.306	0.0985	0.0202	-0.023
	Rusia	0.0274	-0.294	0.2376	0.0356	-0.189	0.1018	0.0210	-0.148
	Turcia	0.0246	-0.065	0.1484	0.0323	0.055	0.0834	0.0186	-0.096
	EM_Index	0.0151	-0.123	0.1008	0.0197	0.014	0.0498	0.0115	-0.093
Frontier markets	Bulgaria	0.0193	-1.456	0.1605	0.0255	-1.536	0.0686	0.0143	0.132
	Croatia	0.0130	-0.199	0.0998	0.0170	0.031	0.0736	0.0098	-0.280
	Estonia	0.0192	0.244	0.0828	0.0193	-0.410	0.1241	0.0190	0.662
	Romania	0.0242	-2.179	0.3358	0.0291	-3.178	0.1285	0.0205	-0.056
	Slovenia	0.0139	-0.404	0.0915	0.0190	-0.282	0.0670	0.0098	-0.231
	Serbia	0.0247	-0.352	0.1725	0.0379	-0.354	0.1233	0.0200	0.450
	FM_Index	0.0104	-1.187	0.0688	0.0127	-1.511	0.0458	0.0088	-0.214

Source: MSCI Barra, calculations made by the authors

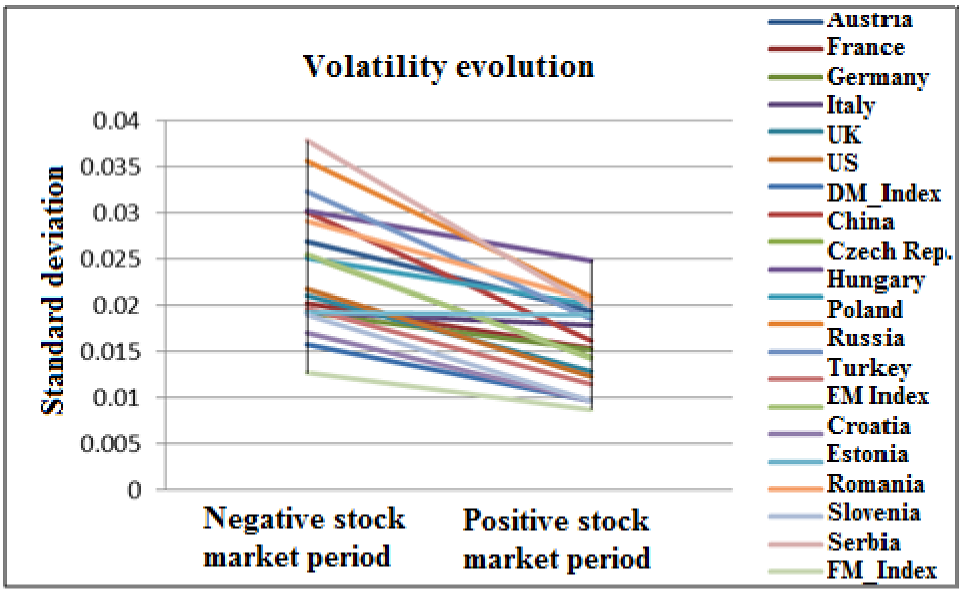

Figure 2.

Source: MSCI Barra, calculations made by the authors

In order to highlight the evolution of the correlation coefficients we used a sample size calculation "rolling" of 130 days (the equivalent of six calendar months of stock trading). The result is shown below in Figure 3 and demonstrates that the value of the correlation coefficient varies over time and their evolution is likely influenced by the stock market situation. For example we observe that during periods of declining stock markets (2007-2008 and then the end of 2010 until mid 2011) the intensity of correlations between all types of markets has been growing, while during periods of an upward trend (2009 and early 2012) the correlation coefficient values are reduced.

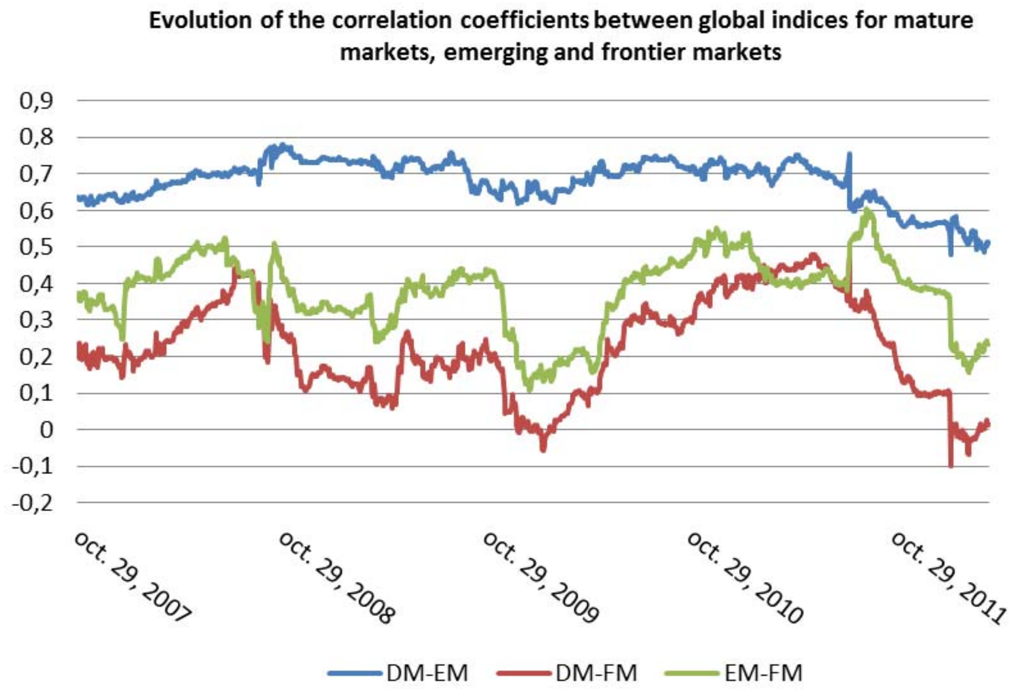

Figure 3. Source: MSCI Barra, calculations made by the authors

We test the presence of the phenomenon of autocorrelation for daily returns by using AC functions ("autocorelation") and CAP ("partial-autocorelation"), for correlations between the current returns and the previous 100 past returns, for all the 21 assets that were analyzed. The values of autocorrelation coefficients and partial autocorrelation respectively show that the phenomenon of autocorrelation in daily returns is not present.

In the second part of the paper we analyze the behavior of low frequency returns (using monthly data) for the 21 assets. Similar to the approach in the first part of this paper, we have calculated the average, variance, the coefficient of asymmetry (skewness) and the flattening coefficient (kurtosis) for the monthly returns. The results are presented in Table 5 below.

As it can also be observed in the case of the monthly returns, we do not have enough statistic arguments to affirm that the average is not equal to zero. This is confirmed both by the values offered in the table and by the t-statistic test applied to each of the 21 monthly time series. At same the time, similar to the situation of the daily returns, the F statistical test (ANOVA and Welch variants) indicate that the value of the averages are equal for all 21 series of monthly returns that were analyzed.

Table 5. Descriptive statistics for the series of monthly returns

		Average	Median	Max	Min	Std. Dev.	Skew-ness	Kurto - sis	Jarque-Bera	p-value
MM	Austria	-0.0197	-0.0150	0.1758	-0.3650	0.0997	-1.07	5.22	23.3857	0.000
	France	-0.0085	-0.0087	0.1197	-0.1517	0.0594	-0.36	2.74	1.4339	0.488
	Germany	-0.0045	0.0057	0.1451	-0.2075	0.0681	-0.68	3.75	5.9795	0.050
	Italy	-0.0164	-0.0233	0.1714	-0.1672	0.0684	0.04	2.97	0.0151	0.992
	UK	-0.0055	0.0010	0.1167	-0.1216	0.0518	-0.32	2.91	1.0090	0.604
	UD	-0.0002	0.0010	0.0922	-0.1029	0.0469	-0.36	2.45	1.9981	0.368
	DM_INDEX	-0.0027	0.0029	0.1055	-0.1090	0.0463	-0.39	2.92	1.5453	0.462
Emerging markets	China	0.0021	0.0116	0.1605	-0.2555	0.0865	-0.76	3.41	6.1297	0.047
	Czech Rep.	-0.0039	-0.0074	0.1685	-0.2465	0.0721	-0.37	4.66	8.1727	0.017
	Hungary	-0.0116	0.0069	0.2259	-0.4660	0.1185	-0.96	5.37	22.7556	0.000
	Poland	-0.0092	-0.0014	0.2356	-0.3110	0.0992	-0.33	4.00	3.5361	0.171
	Russia	-0.0049	0.0117	0.1997	-0.3327	0.1064	-0.65	3.54	4.9252	0.085
	Turkey	-0.0005	0.0033	0.2588	-0.3183	0.1182	-0.23	3.52	1.1591	0.560
	EM_Index	0.0016	0.0068	0.1528	-0.2193	0.0695	-0.69	3.83	6.3317	0.042
Frontier markets	Bulgaria	-0.0326	-0.0108	0.2339	-0.5339	0.1179	-1.60	8.22	92.0749	0.000
	Croatia	-0.0115	-0.0154	0.1835	-0.2659	0.0754	-0.63	5.78	22.8355	0.000
	Estonia	-0.0117	0.0062	0.4322	-0.3796	0.1158	0.34	6.61	33.2325	0.000
	Romania	-0.0146	0.0186	0.2774	-0.5980	0.1423	-1.40	6.71	52.9945	0.000
	Slovenia	-0.0163	-0.0108	0.1645	-0.1712	0.0622	-0.37	4.11	4.3181	0.115
	Serbia	-0.0278	-0.0071	0.3537	-0.6457	0.1719	-1.13	5.99	26.8283	0.000
	FM_Index	-0.0089	-0.0004	0.1001	-0.1981	0.0600	-0.96	4.63	15.6336	0.000

Source: MSCI Barra, calculations made by the authors

The following conclusion is drawn from Table 5 as the monthly data confirms the hypothesis that the value of the standard deviation is significantly higher than the average. At the same time, 19 of the 21 series of monthly returns validate the property of a skewness figure that has negative values, although these values do not have a large dimension. However in terms of flattening coefficient (kurtosis), we observe that unlike the case of the series of daily returns, the monthly returns offer values that are much closer to the value three (the characteristic value of a normal distribution) for 10 of the 21 active investigation. This observation, together with the previous one according to which the skewness values do not have a large dimension, lead us to expect that the form of monthly returns distribution is closer to the normal distribution, which represents an important value for processing and modeling their behavior.

Indeed, the values of the last column in Table 5 show that the Jarque-Bera test results lead to the conclusion that, for 13 of the 21 series of monthly returns analyzed, the hypothesis in which the distribution is described in a Gaussian waveform can not be rejected at an error level of maximum 1%. We obtain statistical arguments to assert that, for more than half of the series of monthly returns analyzed, the shape of the distribution curve does not differ significantly from the normal (theoretical) distribution.

5. CONCLUSIONS

Our paper investigate the statistical characteristics of daily and monthly returns during April 2007 – March 2012 for 16 European national market indices, 2 international indices and 3 global market indices. We compared the results between three categories: developed markets, emerging markets and frontier markets.

(1) The data that we investigate confirmed that the average of returns is not statistically different from zero. This finding is valid both for daily and monthly returns. Also, it is valid for all the three types of markets (developed, emerging and frontier).

(2) Our results also confirm that standard deviation consistently registers higher values comparing with the average, both for daily and monthly returns. We noticed that the developed markets have lower values for standard deviation in comparison with emerging and frontier markets.

(3) For all the types of markets the distribution of daily returns is significantly different from the normal (theoretical) distribution. At the same time, we found evidence that the lower frequency returns (in our case the monthly returns) tend to have empirical distributions close to the normal (theoretical) distribution. For the developed markets the monthly returns are close to the normal distribution, but the monthly returns of the emerging and frontier markets still differ significantly.

(4) We found negative asymmetry for most of the 21 indices investigated, both for the daily and monthly returns.

(5) The daily returns present excess kurtosis for most of the indices and for all types of markets. This conclusion is also valid for monthly returns from emerging and frontier markets. Not surprisingly, the monthly returns of the developed markets (which we found to have empirical distribution close to the normal distribution) have kurtosis values near 3.

(6) For the daily returns we were able to confirm the „leverage" stylized fact described by Cont R. (2001). More specific, we found that during the high volatility periods, the absolute values of effective returns are also higher. We were unable to test this property for the monthly returns because during the period April 2007 – March 2012 we had only 60 empirical observations for each of the 21 time series.

(7) The study that we have conducted confirms that most of the characteristics of the returns change with time. Especially volatility and correlation coefficient tend to register higher values during market crises and lower values during the periods of positive market evolution. This confirms the hypothesis of contagion between markets. Also, we found that mature markets are highly correlated with other mature markets and less correlated with emerging and frontier markets. On the other hand, the frontier markets tend to have lower correlations both with other frontier markets and with emerging and developed markets.

(8) The daily time series show no autocorrelation of simple logarithmic returns, but present autocorrelations of squared returns. On the other hand, we found that the monthly squared returns tend to be less autocorrelated.

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