UNCERTAINTY IN EU STOCK MARKETS BEFORE AND DURING THE FINANCIAL CRISIS

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Abstract. *The aim of this paper is to study the uncertainty behaviour of the EU stock markets before and during financial crisis by using daily data for main stock market indexes of EU countries. The results show a significant difference in the uncertainty pattern of EU stock markets before and during financial crisis. Also, a large variability among EU stock markets in uncertainty patterns is noticed and this fact could be explained trough inequalities in stock market performances and economic development.*

Keywords: *stable distributions, financial crisis, uncertainty, entropy.*

1. INTRODUCTION

The financial crisis had a severe impact on stock markets across European Union time, following the pattern from US stock market. This impact could be revealed by using a key feature of financial crisis, which is a higher level of uncertainty.

The level of uncertainty of a stock market could be analyzed by using two complementary approaches: information theory and statistical modelling. From an information theory point of view, a robust measure of uncertainty is entropy; in classical form, the Shannon entropy is positively correlated with the level of uncertainty. Also, by using the statistical approach, the probability in the tails of the returns' distribution is an estimate of uncertainty level of a stock market.

As a measure of stock market uncertainty we are using the entropy of the distribution function of returns, while the tail behaviour of returns' distribution is captured by using alpha-stable distributions.

Given the probability distribution of returns is essential for any statistical inference concerning the stock market. In general, the major distribution characterizing the evolution of returns is the normal distribution (Gaussian) or its derivatives (e.g. log-normal distribution).

Recent papers (Rachev et al., 2000 and 2010) show that stable distributions are a much better approach than classical distributions in financial modeling. The fact that the observed distribution of returns is heavy-tailed cannot be explained by a normal distribution.

The relationship between stable distributions and financial crisis has been previously addressed by Barunik, Vacha and Vosvrda (2010). In this study, they are estimating parameters of stable distributions of US and Central Europe stock markets, using daily and intraday data. By analyzing the distribution of returns for 2005-2009, and separately for the periods 2005-2007 (before the financial crisis) and 2007-2009 (the crisis), the authors conclude that there is a significant difference between the probability distribution of returns before and during the financial crisis.

Thus, the pre-financial crisis period does not present large deviation from normal distribution, while the crisis period is characterized by a significant deviation from normality.

In this paper we are using daily data for main stock market indexes of EU-27 countries in order to study the uncertainty behaviour of these stock markets before and during financial crisis.

The study is structured as follows: a first section contains a theoretical presentation of measures of uncertainty, in the second section the main results are presented and the last section is dedicated for conclusions.

2. MEASURES OF UNCERTAINTY

2. 1. Stable distributions

Stable distributions is a class of distributions which have the property of being invariant under linear combinations; Gaussian distribution is a special case of stable distributions.

The difficulty that occurs for stable distributions is that in most cases, an explicit form of probability density function is not known, only the expression of its characteristic function. Thus, a random variable X follows a stable distribution with parameters $(\alpha,\beta,\gamma,\delta)$ (Nolan, 2011) if exists $\gamma > 0, \delta \in \Re$ such as X and $\gamma Z+\delta$ have the same distribution, where Z is a random variable with the following characteristic function:

$$\phi(t) = \mathbf{E}[e^{itZ}] = \begin{cases} \exp(-|t|^{\alpha}[1 - i\beta\tan(\frac{\pi\alpha}{2})sign(t)]), \alpha \neq 1 \\ \exp(-|t|[1 + i\beta t\frac{2}{\pi}sign(t)(\ln(|t|)]), \alpha = 1 \end{cases}.$$

In the above notations $\alpha \in (0.2]$ is the stability index, controlling for probability in the tails (for Gaussian distribution $\alpha = 2$), $\beta \in [-1,1]$ is the skewness parameter, $\gamma \in (0,\infty)$ is the scale parameter and $\delta \in \mathbf{R}$ is the location parameter.

A random variable X follows a stable distribution $S(\alpha,\beta,\gamma,\delta;0)$ if its characteristic function has the following form:

$$\phi(t) = \mathbf{E}[e^{itX}] = \begin{cases} \exp(-\gamma^{\alpha}|t|^{\alpha}[1 + i\beta\tan(\frac{\pi\alpha}{2})sign(t)(|\gamma t|^{1-\alpha} - 1)] + i\delta t), \alpha \neq 1 \\ \exp(-\gamma|t|[1 + i\beta t\frac{2}{\pi}sign(t)(\ln(|\gamma t|)] + i\delta t), \alpha = 1 \end{cases}. \quad (1)$$

A random variable X follows a stable distribution $S(\alpha,\beta,\gamma,\delta;1)$ if its characteristic function has the following form

$$\phi(t) = \mathbf{E}[e^{itX}] = \begin{cases} \exp(-\gamma^{\alpha}|t|^{\alpha}[1 - i\beta\tan(\frac{\pi\alpha}{2})sign(t)] + i\delta t), \alpha \neq 1 \\ \exp(-\gamma|t|[1 + i\beta t\frac{2}{\pi}sign(t)(\ln(|t|)] + i\delta t), \alpha = 1 \end{cases}. \quad (2)$$

Parametrisation $S(\alpha,\beta,\gamma,\delta;1)$ has the advatage that is more suitable for algebric manipulations, altough its characteristic function is not continuous for all parameters.

Parametrisation $S(\alpha,\beta,\gamma,\delta;0)$ is suitable for numerical simulations and statistical inference, altough the expression of characteristic function is more difficult to utilise in algebric calculus. Nolan (2011) shows that the two parametrisations are equivalent; if $X \sim S(\alpha,\beta,\gamma,\delta_1;1)$ and $X \sim S(\alpha,\beta,\gamma,\delta_0;0)$, then

$$\delta_0 = \begin{cases} \delta_1 + \beta\gamma\tan\frac{\pi\alpha}{2}, \alpha \neq 1 \\ \delta_1 + \beta\frac{2}{\pi}\gamma\ln\gamma, \alpha = 1 \end{cases} \quad (3)$$

The behavior of stable distributions is driven by the values of stability index α: small values are associated to higher probabilities in the tails of the distribution.

2.2. Information entropy

Information entropy is the most widely used measure of uncertainty, its applications covering a wide range, from physics to economics and biology. The concept of entropy originates from physics in the 19th century; the second law of thermodynamics stating that the entropy of a system cannot decrease other way than by increasing the entropy of another system. As a consequence, the entropy of a system in isolation can only increase or remain constant over time.

If the stock market is regarded as a system, then it is not an isolated system: there is a constant transfer of information between the stock market and the real economy. Thus, when information arrives from (leaves to) the real economy, then we can expect to see an increase (decrease) in the entropy of the stock market, corresponding to situations of increased (decreased) randomness.

Most often, entropy is used in one of the two main approaches, either as Shannon Entropy – in the discrete case – or as Differential Entropy – in the continuous time case. Shannon Entropy quantifies the expected value of information contained in a realization of a discrete random variable. Also it is a measure of uncertainty, or unpredictability: for a uniform discrete distribution, when all the values of the distribution have the same probability, Shannon Entropy reaches his maximum. Minimum value of Shannon Entropy corresponds to perfect predictability, while higher values of Shannon Entropy correspond to lower degrees of predictability (the minimum value of Shannon Entropy is 0).

Differential Entropy is an extension of Shannon Entropy to the continuous case, but is not a good measure of uncertainty; as it can take negative values and in addition, it is not invariant to some linear transformations.

Dioniso et al. (2006) provide a review of the theoretical and empirical work about the entropy and the variance as measures of uncertainty. Several conclusions could be drawn from this review: first of all, the entropy is a more general measure of uncertainty than the variance or the standard deviation (Philippatos and Wilson, 1972), since the entropy depends on more characteristics of a distribution as compared to the variance and may be related to the higher moments of a distribution (Ebrahimi et al., 1999). Secondly, both the entropy and the variance reflect the degree of concentration for a particular distribution, but their metric is different. While the variance measures the concentration around the mean, the entropy measures the diffuseness of the density irrespective of the location parameter (Ebrahimi, Maasoumi and Soofi, 1999).

In this paper we use a recently developed concept, the entropy of a function (Lorentz, 2009) in order to estimate the entropy of a distribution function,by employing very general assumptions and in a non-parametric context.

Basically, our methodology involves the following steps *to estimate the entropy of a distribution function (Lazar et al.(2011)). For a sample $X_0,...., X_{n-1}$ of i.i.d. observations drawn form the distribution F:*

Step 1. Estimate the distribution function using a Kernel Estimator or Empirical Distribution Estimator, obtaining values $\hat{F}_n(X_i)$ for $i = 0,..,n-1$;

Step 2. Sampling from the distribution function, using the sampled function $S_n(\hat{F}_n)(i) = \hat{F}_n(X_i)$ for $i = 0,..,n-1$;

Step 3. Define a quantum $q > 0$; then

$Q_q S_n(\hat{F}_n)(j) = (i+1/2)q$, if $\hat{F}_n(X_j) \in [iq,(i+1)q)$;

Step 4. Compute the probabilities

$$p_n(i) = \frac{c_n(i)}{\sum_j c_n(j)} = \frac{c_n(i)}{n} = \frac{card\{\hat{F}_n(X_j) \in [iq,(i+1)q)\}}{n};$$

Step 5. The estimator of entropy of distribution function is then:

Step 6. $H_q(\hat{F}_n) = -\sum_i p_n(i)\log_2 p_n(i)$. (4)

In order to insure comparability among various distributions, one can define a normalized entropy,

as a ratio between the entropy and the entropy of uniform distribution:

$NH_q(\hat{F}_n) = -\sum_i p_n(i)\log_2 p_n(i)/\log_2 n \in [0,1]$. (5)

In the following we will refer to entropy as the normalized entropy, taking values between 0 and 1.

Low values of entropy are associated with heavy-tailed distributions, while high values of entropy correspond to Gaussian distribution. In other words, as the tails probability is higher, the expected value of entropy is lower.

3. DATA AND EMPIRICAL RESULTS

In order to asses the impact of financial crisis on uncertainty behavior of stock market indexes for EU countries, we use a sample of daily observations for 26 European countries. Starting from observed index ? p_t, we compute the logreturns as $r_t = \log p_t - \log p_{t-1}$ and using the methodology described above, we estimate the entropy of the returns distribution function and also the stability index α for stable distribution (we use STABLE. EXE, available on http://academic2.american.edu/~jpnolan /stable/stable.html)

Stock market indexes

Table no. 1.

Country	Country code	Index	2005/ 2007 Entropy	2008/ 2010 Entropy	2005/ 2007 α	2008/ 2010 α
Malta	MT	MSE	0.613	0.640	1.283	1.373
Bulgaria	BG	SOFIX	0.693	0.622	1.414	1.371
Slovenia	SI	SBITOP	0.661	0.590	1.482	1.501
Cyprus	CY	CYSMMAPA	0.593	0.742	1.578	1.809
Lithuania	LT	VILSE	0.669	0.565	1.590	1.443
Portugal	PT	PSI20	0.589	0.528	1.629	1.592
Ireland	IR	ISEQ	0.642	0.645	1.641	1.682
Latvia	LV	RIGSE	0.597	0.675	1.663	1.695
Sweden	SE	OMX Stockholm	0.675	0.687	1.668	1.655
Denmark	DK	OMX Copenhagen	0.675	0.692	1.668	1.657
Romania	RO	BET	0.584	0.659	1.680	1.637
UK	UK	FTSE100	0.687	0.614	1.682	1.598
Belgium	BE	BEL20	0.751	0.654	1.706	1.714
Czech Republic	CZ	PX50	0.609	0.559	1.718	1.572
Austria	AT	ATX20	0.617	0.672	1.729	1.672
Greece	GR	ASE	0.633	0.719	1.741	1.808
Luxemburg	LU	LUXX	0.596	0.642	1.770	1.738
Netherlands	NL	AEX	0.744	0.631	1.773	1.566
Spain	ES	IBEX	0.729	0.601	1.776	1.684
Finland	FI	OMXH15	0.813	0.701	1.805	1.724
Poland	PL	WIG	0.694	0.706	1.854	1.667
France	FR	CAC40	0.787	0.634	1.857	1.648
Italy	IT	FTSEMIB	0.752	0.649	1.858	1.671
Hungary	HU	BUX	0.775	0.610	1.871	1.699
Germany	DE	DAX	0.809	0.630	1.881	1.620

The results obtained for the two subsamples show significant differences between EU countries from the point of view of stock market uncertainty.

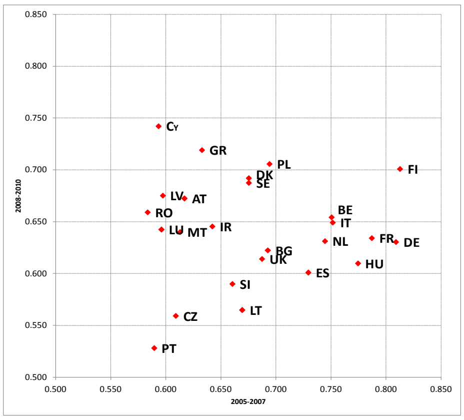

Fig. 1. Behavior of entropy : 2005-2007 vs 2008-2010

Thus, for 2005-2007 period, before the financial crisis, one can distinguish three clusters of countries, based on entropy behavior:

- first cluster – countries with low uncertainty (high entropy) is formed by the following countries: Finland, Germany, France, Hungary, Netherlands, Italy, Belgium, Spain;
- second cluster – countries with moderate uncertainty is formed by the following countries: Lithuania, UK, Bulgaria, Poland, Denmark, Sweden, Slovenia;
- third cluster – countries with high uncertainty is formed by the following countries: Portugal, Greece, Czech Republic, Malta, Luxembourg, Romania, Cyprus, Latvia, Ireland.

The situation is slighly different in period 2008-2008 (financial crisis): for the entire sample of countries, entropy is lower than in period 2005-2007, indicating an increased likelihood of extreme events on stock market and a higher degree of uncertainty.

Thus, for 2008-20010 period, during the financial crisis, one can distinguish three clusters of countries, based on entropy behavior:

- first cluster – countries with low uncertainty (high entropy) is formed by the following countries: Greece, Cyprus, Poland, Finland;
- second cluster – countries with moderate uncertainty is formed by the following countries: Germany, France, Hungary, Netherlands, Italy, Belgium, Spain, UK, Bulgaria, Denmark, Sweden, Greece, Malta, Luxembourg, Romania, Cyprus, Ireland;
- third cluster – countries with high uncertainty is formed by the following countries: Portugal, Czech Republic, Lithuania, Slovenia.

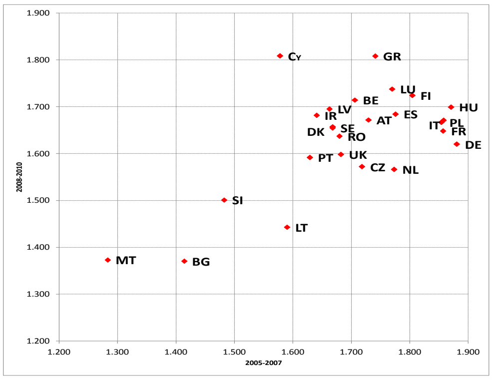

Fig.2. Behavior of α (stability index):2005-2007 vs 2008-2010

The estimation of stability index α of the stable distribution shows a different clustering behavior of EU stock markets: for most of the countries, there is a departure from normality induced by the financial crisis. Two extreme clusters could be identified based on this criterion:

- countries with extreme departure from normality: Malta, Bulgaria, Slovenia, Lithuania;
- countries for which stability index α shows a behavior close to Gaussian distribution: Greece and Cyprus.

Return and volatility

Table no. 2. - %-

Country	Country Code	Index	2005/2007 Return	2008/2010 Return	2005/2007 Volatility	2008/2010 Volatility
Malta	MT	MSE	0.068	-0.033	0.879	0.795
Bulgaria	BG	SOFIX	0.137	-0.212	1.035	1.841
Slovenia	SI	SBITOP	0.133	-0.144	0.878	1.492
Cyprus	CY	CYSMMAPA	0.206	-0.203	1.523	3.021
Lithuania	LT	VILSE	0.079	-0.031	0.986	1.654
Portugal	PT	PSI20	0.064	-0.091	0.678	1.859
Ireland	IR	ISEQ	0.015	-0.115	1.081	2.300
Latvia	LV	RIGSE	0.049	-0.055	0.975	1.895
Sweden	SE	OMX Stockholm	0.050	0.009	1.106	1.933
Denmark	DK	OMX Copenhagen	0.050	0.009	1.106	1.943
Romania	RO	BET	0.110	-0.083	1.709	2.434
UK	UK	FTSE100	0.039	-0.012	0.844	1.730
Belgium	BE	BEL20	0.045	-0.061	0.841	1.754
Czech Republic	CZ	PX50	0.075	-0.052	1.146	2.237
Austria	AT	ATX20	0.083	-0.059	1.169	2.365
Greece	GR	ASE	0.083	-0.174	1.022	2.257
Luxemburg	LU	LUXX	0.083	-0.059	0.941	1.949
Netherlands	NL	AEX	0.051	-0.049	0.840	1.979
Spain	ES	IBEX	0.067	-0.057	0.850	2.027
Finland	FI	OMXH15	0.033	-0.010	1.252	2.096
Poland	PL	WIG	0.098	-0.021	1.199	1.664
France	FR	CAC40	0.050	-0.051	0.909	1.952
Italy	IT	FTSEMIB	0.029	-0.085	0.822	2.010
Hungary	HU	BUX	0.077	-0.016	1.408	2.258
Germany	DE	DAX	0.084	-0.020	0.908	1.842

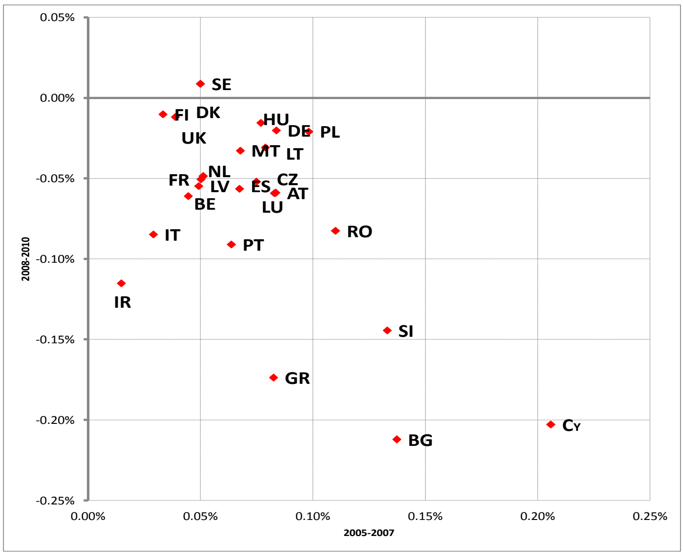

Fig. 3. Performance of stock market: 2005-2007 vs 2008-2010

The analysis of the European stock markets could be performed also in terms of performance (returns) and volatility; what financial crisis brings from the point of view of stock market performance is a significant drop in average daily returns and also a significant increase in volatility.

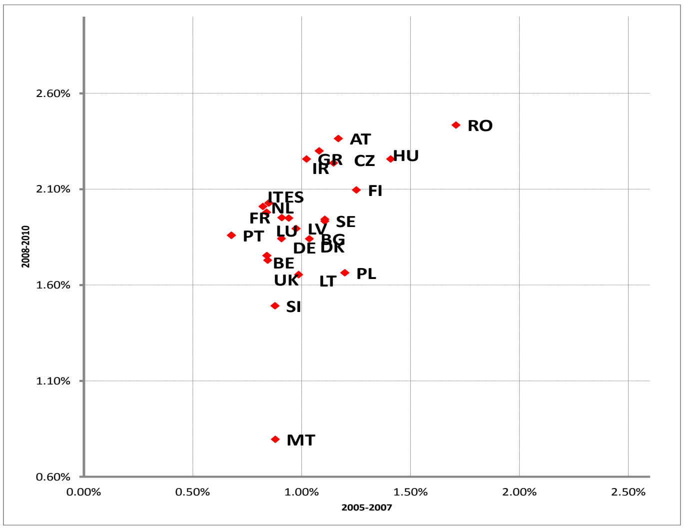

Fig. 4. Volatility of stock market: 2005-2007 vs 2008-2010

From the point of view of average daily returns before and during the financial crisis, most of European stock markets have a similar behavior, with few notable exceptions: Greece, Cyprus, Bulgaria and Slovenia. For these countries, the financial crisis had a severe impact on stock market performance; for example, Cyprus had a drop in average daily return from 0.2% to -0.2%, while Greece average daily return dropped from 0.08% to -1.7%.

Also in terms of volatility, both before and during financial crisis, we can observe a cluster of countries with the highest volatilities: Greece, Austria, Romania, Ireland, Hungary, Czech Republic, Finland, Hungary.

As the above results show, the impact of financial crisis on European stock markets was not uniform across countries; there are significant differences in terms of performance, volatility, uncertainty and behavior towards normality.

4. CONCLUSIONS

Using daily data for main stock market indexes of EU-27 countries, we have studied the behaviour of these stock markets before and during the financial crisis.

The analysis was conducted on two directions, looking for significant differences between properties of return distribution and also looking for homogenous groups of countries based on stock market indicators.

From a distributional point of view, most of the countries exhibit large departure from normality during financial crisis, values of stability index α being significantly lower than 2(the case of Gaussian distribution).

The same conclusion was revealed using entropy of distribution function of returns as an estimator of stock market uncertainty. For majority of countries form our sample, there is a clear movement towards high uncertainty levels during financial crisis.

Further research need to be conducted in order to explain this large variability among European stock markets in terms of uncertainty patterns, perhaps trough existing inequalities in stock market and economic development.

5. ACKNOWLEDGMENTS

This paper was cofinanced from the European Social Fund, through the Human Resources Development Operational Sectorial Program 2007-2013, project number POSDRU/89/1.5/S/59184, „Performance and excellence in the post-doctoral economic research in Romania”.

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