Shock transmission among the European Stock markets

Radu Lupu[1], Institute for Economic Forecasting, Romania

Abstract. The analysis of the comovements of stock market returns was approached with many modeling techniques ranging from the simple and GARCH style dynamic conditional correlation to multivariate GARCH and studies of the bivariate distribution. The quest for the analysis of the now standardized concept of international contagion made room for the employment of all these techniques. Our paper focuses on the analysis of the comovements in the volatilities of the returns of stock market indices from the most important developed and emerging European countries, using different forms of computation for different frequencies, starting from intra-day 5-minute returns to weekly returns (data used from Bloomberg). After a brief characterization of the distribution of returns and a reconfirmation of the stylized facts for the European emerging markets we focus on the clustering effect of volatilities, in the attempt to identify the moments when a new cluster is formed, i.e. when the volatilities change their size (from small to big or from big to small). The analysis of these events for the respective countries intends to reveal the mechanism of international information transmission. The paper also fits a jump-diffusion process, along the lines of Maheu and McCurdy (2007) adjusted for the series of volatilities, where the Poisson process characterizes the time until a change in the volatility cluster occurs.

Keywords: comovement, returns' volatility, European emerging stock markets

JEL classification:C39, G15

1 Introduction

Even if the process of financial globalization has not followed a linear trend over time, and the exact timing of financial liberalization remains somewhat controversial, there is a broad consensus among economists that capital markets are much moreintegrated today than they were 30 years ago.

Over the years, many papers have contributed to the very important debate onthe interaction across international stock markets, looking at volatility spillovers, correlation breakdowns, trends in correlation patterns. The integration of the financial markets wore down muchof the gains from international diversification which rely on low correlations across internationalstock markets. The intensity of the comovements and spillovers effects driven by the financial integration may increase the risk of global financial instability.

Most studies into comovements in stock markets have focused on developed economies. Lately there has been a growing body of empirical research on emerging capital markets, partly in response to the diversifying activities of multinational enterprises in these markets, and as a result of the growing interest shown by private and large institutional investors seeking to diversify their portfolios in international capital markets. International differences in the institutional framework of emerging market economies may playan important role on the magnitude of shocks transmitted across countries.

When one compares US with European stock markets, that have different trading hours, we can observe the international transmission mechanism. When New York stock market opens its business day, many things already happened on the European stock market. Similarly, European brokers take into account how New York market ended. These equity markets are linked through trade and investment and because of that, any change about economic fundamentals in one region can have implications for the other one. In the same time, both foreign exchange markets and national stock markets share a number offacts for which a satisfactory explanation is still missing in standard theoriesof financial markets.

In this paper the analysis of the comovements of stock market returns was approached with many modeling techniques ranging from the simple and GARCH style dynamic conditional correlation to multivariate GARCH and studies of the bivariate distribution. The paper investigates the behavior of stock market indexes in two respective ways: on one hand, we study the properties of the jumps (outliers) for the high-frequency stock market returns when

[1]This paper benefited by financial support from the project *The economic scientific research, support for the human welfare and development in the European context*, financing contract no.POSDRU/89/1.5/S/62988, financed by European Social Fund through Sectoral Operational Programme Human Resources Development 2007-2013.

we look at many European indexes and, on the other hand, we try to capture the behavior of the co-movement of the volatilities of these indexes at the same frequency.

This paper is organized as follows. In Section 2, is presented the literature review. In Section 3, a dataoverview and methodology are provided and in Section 4 the empirical results are discussed. Finally, Section 5 concludes.

2 Literature review

Economists have been studyingwhy there is propagation of volatility from one market to another, since alongtime.Grubel (1968) is a most sited paper representing the start of researches in the field of stock market returns comovement. Since that, the analysis of the benefit of international portfolio diversification and of the stock market synchronization received a special attention in international finance.

Bekaert and Harvey (1995), Forbes and Rigobon (1999) are only some important paper that investigate the cross-country linkages between stock markets. As a matter of fact, a growing body of literature has emerged more recently on the issue of international stock pricescomovement (King et al., (1994), Lin et al. (1994), Longin and Solnik (1995, 2001), Karolyi and Stulz (1996), Forbes and Rigobon(2002), Brooks and Del Negro (2005, 2006)). In particular, most of those studies have found that the comovement of stock returnsis not constant over time. Evidence of increasing international comovement of stock returns since the mid-90s among the major developed countries, was found by Brooks and Del Negro (2004) and Kizys and Pierdzioch (2009).

The determinants of the cross-country financial interconnections are split in trade intensity factors (Chinn and Forbes, 2004), financial development factors (Dellas and Hess, 2005), business cycle synchronization factors (Walti, 2005), and geographical variables (Flavin et al., 2002). The divergence of the results and main conclusions can be partly explained by the high degree of heterogeneity [2] in the empirical approaches adopted by the literature. However, the comovement analysis should also take into account the distinction between the short and long-term investor (Candelon et al. (2008)).

The comovement of stock returns was evaluated usually through the correlation coefficient while the evolving properties have been investigated either through a rolling window correlation coefficient as in the study of Brooks and Del Negro (2004) or by considering nonoverlapping sample periods like in the paper of King and Wadhwani (1990) and Lin et al. (1994).Morana andBeltratti (2008) found strong linkagesacross European, the US and the Pacific Basin stock markets, involving comovements in prices, returnsand volatility over the period 1973–2004. Their results show that the heterogeneity between Europe and the US has steadily reduced, these markets being currently strongly integrated.

Applying a new technique, the wavelet analysis, that allow for time and frequency simultaneous characterization, Rua and Nunes (2009) focused on Germany, Japan, UK and US stock markets over the last four decades. A noteworthy finding of their paper is that the strength of the comovement ofinternational stock returns depends on the frequency. The authors argue that the comovement between markets is stronger at thelower frequencies suggesting that the benefits from international diversification may be relatively less important in the long-term than in the short-term and that the strength of the comovement in thetime-frequency space varies across countries as well as across sectors.Taking into account that the United States was the crises epicenter, Didier and all (2010) analyzed the factors driving the comovement between US and 83 countries stock returns, differentiating the periods before and after the collapse of Lehman Brother. The authors have argued that there is evidence of a “wake-up call” or “demonstrationeffect” in the first stage of the crisiswhere investorsbecame aware that certain vulnerabilities present in the US context could put other economies atrisk, because countrieswith vulnerable banking and corporate sectors exhibited higher comovement with the US market, the main transmission channel being the financial one.

Thestock exchanges from Central and Eastern European countriesperform in a quite different manner as compared to developed markets. First studies that specified these differences are Barry, Peavy III and Rodriguez (1998), Harvey (1995), Divecha, Drach and Stefek (1992), as well as Bekaert et al. (1998). The literature evidenced

[2]Heterogeneity is observed in the sample of included countries (developed vs. developing countries), the nature of the econometric approach (cross-sectional vs. time-series), the measurement of market comovement, and the nature and measurement of explanatory factors.

a number of empirical regularities: high volatility, low correlations with developed markets and within emerging markets, high long-horizon returns, and more variability in the predictability power as compared to the returns of the stocks traded in the developed markets. It is also well evidenced that emerging markets are more likely to experience shocks induced by regulatory changes, exchange rate devaluations, and political crises.

Pajuste (2002) observes that Central and Eastern European capital markets are quite different in terms of their correlations with European Union capital markets. While the Czech Republic, Hungary and Poland display higher correlations among them and with the European Union market, Romania and Slovenia show inexistent or even negative correlation with the European Union capital market. A stock market convergence of Central andEastern European (CEE) countries to the rest of Europe was studied furthermore by Harrison and Moore (2009), using threeapproaches to obtain time-varying estimates of thecomovement between returns: realized correlation analysis, rolling unit root tests, andrecursive cointegration tests.The results suggest that there is arelatively weak correlation between stock markets in CEE countries and those in Europe, with the link between the exchanges strengthening since 2002.Analysis in this area are realized as well by Horobet and Lupu (2009) and Lupu and Lupu (2009) showing the properties of these correlations with different techniques – cointegration and Granger causality tests on one hand and dynamic conditional correlations performed at the burst of the actual crisis on the other hand.

Harrison, Lupu and Lupu (2010) identified in their paper the statistical properties of the Central and Eastern European stock market dynamics. The paper focuses on the stock market indices of ten emerging countries from the Central and Eastern European region – Slovenia, Slovak Republic, Estonia, Latvia, Lithuania, Bulgaria, Czech Republic, Romania, Hungary and Poland –over the 1994-2006 period and present evidence of stationarity for the returns of these indices and identified some common characteristics of these markets taken as a whole.

The international transmission of stock returns and volatility was investigated by Lin, Engle and Ito (1994) usingintradaily data that define Tokyo and New York markets. They argue that information revealed duringthe trading hours of one market has a globalimpact on the returns of the other market and that the interdependencein returns and volatilities is generally bi-directional.

As stipulated in the literature (Soydemir (2000)), emerging markets respond morequickly to shocks originating in their own market than from foreign market disturbances and the emerging market economies thathave opened their markets to achieve greater financial integration are more prone to externalshocks.

Current research has documented the importance of jump dynamics in combinationwith autoregressive volatility for modeling returns. Jorion (1988), Andersenet al. (2002), Chib et al. (2002), Eraker et al.(2003), Chernov et al. (2003), and Maheuand McCurdy (2004) are only a few examples. Jumps provide auseful addition to stochasticvolatility models by explaining occasional, large abrupt moves in financialmarkets,accounting for neglected structure, but they are generally not used to capture volatility clustering. Maheu and McCurdy (2007)proposed a new discrete-time model of returns in which jumps capture persistence in the conditional variance and higher-order moments and the evaluation focuses on the dynamics of theconditional distribution of returns using density and variance forecasts. The empirical results indicate that the heterogeneous jump model effectively captures volatilitypersistence through jump clustering and that the jump-size variance isheteroskedastic and increasing in volatile markets.

3 Data and methodology

The data that we used consists of five-minute stock market index returns from some of the developed European markets as well as the Eastern markets: DAX (Germany), CAC (France), UKX (UK), IBEX (Spain), SMI (Switzerland), FTSEMIB (Italy), PSI20 (Portugal) ISEQ (Ireland), ATX (Austria), WIG (Poland), PX (Czech Republic), BUX (Hungary), BET (Romania) and SBITOP (Slovenia). The period we took into account was from the 3rd of August 2010 until the 10th of February 2011.

The trading sessions are different in the countries in our analysis (some start at 8:00 hours, local time, others start at 8:30 and they tend to stop at different moments) and this is why, since we are interested in studying the co-movement of these returns, we had to build a database that identifies the moments in time when all the indexes were traded. Another issue was that the high frequency returns tend to have a small size and at the turn of the day we may find higher values for the returns. This is why we decided to take out of the sample the returns that were recorded at the change of the day (the returns from the value of the index at the end of the day to the value of the index at the beginning of the next day). Therefore, our returns are not presumed to show any jumps (outliers) caused by the accumulation of information between trading sessions.

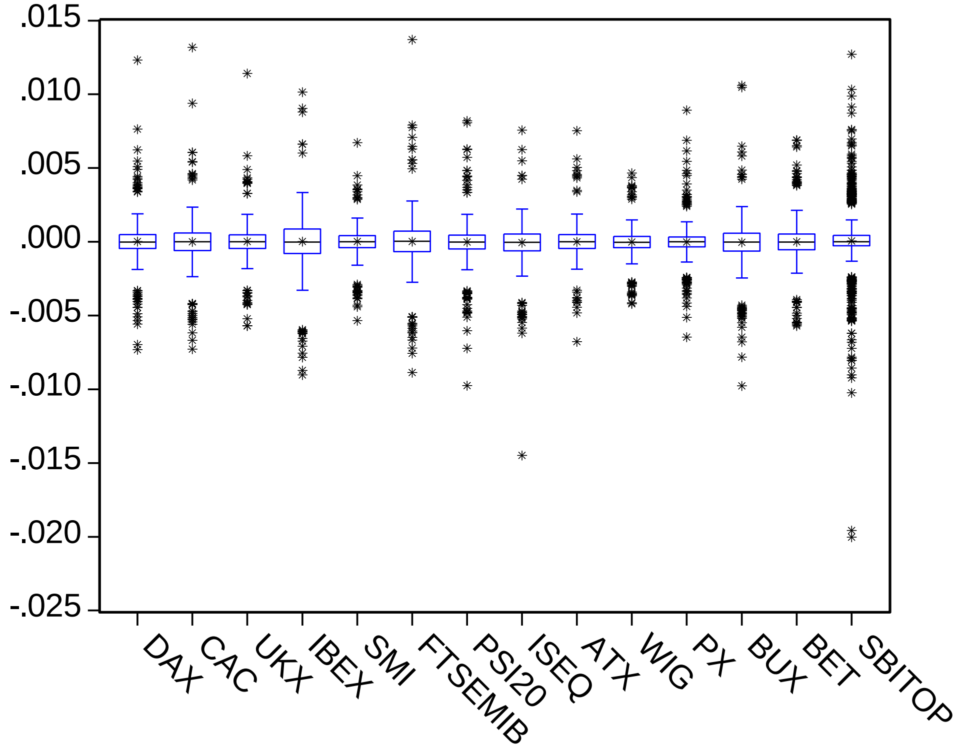

Figure 1. The distribution of the five-minute returns: medians, means and outliers

In terms of methodology, we started the analysis with the identification of outliers in sense of finding the moments when the returns were outside a 95% confidence interval for each of the stock index. Next, we simply made an analysis of the simultaneity of the jumps for the common sample of all the indexes. The results of this analysis are provided in the next section.

The following step was to use a Dynamic Conditional Correlation GARCH-like model (DCC) to fit the changes in the correlations of the returns for the five-minute frequency. The dynamical correlations as well as the GARCH estimates of the volatilities were then used to characterize the co-movement of the high-frequency returns.

The specification of the DCC model starts from the GARCH-like specification

$$\sigma_{ij,t+1}^2 = \omega + \alpha R_{i,t} R_{j,t} + \beta \sigma_{ij,t}^2 ,$$

which makes the correlations between returns i and j to be:

$$\rho_{ij,t+1} = \frac{\omega + \alpha R_{i,t} R_{j,t} + \beta \sigma_{ij,t}^2}{\sqrt{(\omega + \alpha R_{i,t}^2 + \beta \sigma_{i,t}^2)(\omega + \alpha R_{j,t}^2 + \beta \sigma_{j,t}^2}}$$

Standardizing each return by its dynamic standard deviation, we get

$$z_{i,t+1} = \frac{R_{i,t+1}}{\sigma_{i,t+1}}$$

We notice the conditional covariance of news equals the conditional correlation of the raw returns

$$E_t\left(z_{i,t+1}z_{j,t+1}\right)=E_t\left(\left(\frac{R_{i,t+1}}{\sigma_{i,t+1}}\right)\left(\frac{R_{j,t+1}}{\sigma_{j,t+1}}\right)\right)=\frac{E_t\left(R_{i,t+1}R_{j,t+1}\right)}{\sigma_{i,t+1}\sigma_{j,t+1}}=\frac{\sigma_{ij,t+1}}{\sigma_{i,t+1}\sigma_{j,t+1}}=\rho_{ij,t+1}$$

Thus modelling the conditional correlation of the raw returns is equivalent to modelling the conditional covariance of the standardized returns. We can consider GARCH(1,1) type specifications of the form

$$q_{ij,t+1}=\bar{\rho}_{ij}+\alpha\left(z_{i,t}z_{j,t}-\bar{\rho}_{ij}\right)+\beta\left(q_{ij,t}-\bar{\rho}_{ij}\right).$$

In estimating the dynamic conditional correlation models suggested above, we can rely on the quasi maximum likelihood estimation (QMLE) method.

The next step in our analysis consisted in the calibration of a VAR model on the volatilities of the high-frequency returns, which were proxied by the squared returns. The specification of the VAR model on volatilities was constructed to allow for 1 lag dependence among the 14 variables taken into account. The results are provided in the next section as well.

The last step in our analysis consisted in the calibration of a jump process in the specification of Maheu and McCurdy (2007). The specification is presented in the following lines.

$$r_t=\mu+\sigma z_t+J_t\xi_t, \quad z_t\sim N(0,1)$$

$$\xi_t\sim N\left(\mu_J,\sigma_{J,t}^2\right), \quad J_t\in\{0,1\}$$

$$P(J_t=1|\omega_t)=\lambda_t \text{ and } P(J_t=0|\omega_t)=1-\lambda_t$$

$$\lambda_t=\frac{\exp(\omega_t)}{1+\exp(\omega_t)}$$

$$\omega_t=\gamma_0+\gamma_1\omega_{t-1}+u_t, \quad u_t\sim NID(0,1), \quad |\gamma_1|<1$$

$$\sigma_{J,t}^2=\eta_0+\eta_1X_{t-1}$$

r_t – returns for the period t = 1,…,T

μ – the mean of the returns when there is no rare event (no jump)

J_t – indicates the occurrence of the jump (J_t = 1 means that we will observe a jump at moment t; if J_t = 0 there is no jump at moment t)

λ_t – the probability to have a jump at moment t i.e. $Pr(J_t = 1)$

ξ_t – the size of a possible jump at moment t

μ_J – the mean for the jump-size variable

$\sigma_{J,t}^2$ – the variance of the jump-size variable

X_{t-1} – the absolute value of r_{t-1} which allows the variance $\sigma_{J,t}^2$ to be positive.

The estimation of the model was realized through the Markov Chain Monte Carlo using a Gibbs algorithm. In the analysis realized by Maheu and McCurdy (2007) the vector of parameters θ = {μ, σ^2, μ_J, η, γ}, where η ={η_0, η_1} and γ ={γ_0, γ_1} is augmented with the unobserved state vectors ω ={ω_1, …, ω_T}, jump times J = {J_1, …, J_T} and the jump sizes ξ = {ξ_1, …, ξ_T}.

We compute the conditional densities for all the parameters and run 5000 simulations with draws from these densities by the following algorithm:

1. sample μ | θ-μ,i-1 ω i-1, Ji-1, ξ i-1, r
2. sample σ^2 | θ- σ^2 i-1, ω i-1, Ji-1, ξ i-1, r
3. sample μ_J | θ- μ_J i-1 , ω i-1, Ji-1, ξ i-1, r
4. sample η | θ- η i-1, ω i-1, Ji-1, ξ i-1, r
5. sample blocks $\omega_{(t,\tau)}$ |θ- $\omega_{(t,\tau)}$ i-1, ω i-1, Ji-1, ξ i-1, r
6. sample γ |θ- γ i-1, ω i, Ji-1, ξ i-1, r
7. sample ξ | θ i, ω i, J i-1, r
8. sample J | θ i, ω i, ξ i, r
9. goto 1

where r = {r1, …, rT} and i is the iteration number.

4 Results

In terms of co-movements, the most interesting issues observed in our analysis deal with the fact that, in case we take into account only the values that are outside a very conventional 95% confidence interval (two sigmas away from the mean in both directions) we notice that for this high frequency data these events are happening usually simultaneously for all the indexes in our database. In case we consider these to be jumps, then our dynamics show a close co-movement of the stock markets in Europe.

On average, we found that, out of the 14 indexes that we took into account, for a 5-minute frequency, we have about 10.15 of them happening in the same time. We consider this to be a proof of co-movement, showing the fact that usually, when unusual returns are realized in the stock markets, they have the tendency to be realized in the mean time for all the stock markets, showing that the information is moving in a fast manner around Europe and also showing that the large movements are probably the cause of important information affecting the whole environment, since many of them are reacting in a five-minute interval.

In order to produce a better characterization of the structure of the outliers (jumps) and, in the same time, reveal the properties of the co-movements, we organized the data to compute the number of situations in which we had simultaneous outliers out of the whole sample of indexes taken into account.

1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**
52.43 %	6.60%	4.86%	4.17%	4.17%	4.17%	1.39%	4.86%	3.82%	3.13%	2.78%	1.04%	5.90%	0.69%
-8.15E-05	-1.02E-03	1.80E-03	-1.39E-03	1.47E-03	2.68E-03	-2.37E-03	-2.50E-03	1.23E-03	3.61E-03	7.20E-03	-1.08E-02	4.45E-04	2.79E-03

Table1: The percentage of simultaneous outliers out of all the situations when we experienced outliers in the sample of our stock market index returns

As we can notice from the above table, out of a number of 288 moments when outliers were recorded (from a sample of 2413 records at the five-minute frequency), a high number (52.43%) happened in isolated situations, i.e. only one stock index experienced the outlier, but we notice that almost half of the outliers were experienced in at least 2 situations, with a lot of them happening in 8 and mostly 13 stock markets in the same time. Important evidence is also the fact that, when taking into account the mean values of the outliers, the ones that are isolated (only one index exhibiting a jump) are the smallest, while for the others we see higher absolute values. This can be considered to be a proof of the fact that usually the big jumps tend to spread, while the ones that are not so big tend to be local and, on the other hand, this difference in size also might explain the bigger number of isolated jumps, since a smaller size means that they are closer to the mean and, hence, they tend to have a higher frequency (higher rate of realization).

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**
Germany	3	11	21	8	25	58	75	71	91	89	88	100	100	100
France	2	11	14	8	25	50	75	71	91	100	100	100	100	100
UK	2	0	21	33	50	58	50	57	91	89	75	100	100	100
Spain	2	11	14	25	25	25	75	71	73	67	75	100	100	100
Switzerland	3	32	14	33	33	50	75	64	73	89	88	100	88	100
Italy	1	21	21	33	42	8	75	64	64	78	88	100	100	100
Portugal	5	11	21	17	17	42	50	50	64	67	100	100	100	100
Ireland	1	16	43	50	25	33	50	50	64	67	50	67	94	100
Austria	2	5	7	33	67	50	50	57	55	89	88	67	100	100
Poland	7	0	36	42	42	58	50	50	64	56	75	67	100	100
Czech Republic	3	21	7	17	50	50	75	50	73	89	88	100	100	100
Hungary	3	21	29	50	42	42	0	43	45	56	100	100	100	100
Romania	12	11	36	25	17	33	0	71	27	44	75	100	88	100
Slovenia	54	32	14	25	42	42	0	29	27	22	13	0	29	100

Table 2: The frequency of outliers for each stock market index (in percentage)

The previous table shows the proportion of outliers in which each of indexes was involved out of the number of all the outliers identified in the sample. Hence, we can say that, out of all the situations in which we had only one outlier in the whole sample, which was not accompanied in the same moment by another outlier, there were only 3% of these situations in which Germany was involved (in only 3% of the cases Germany had an isolated outlier). Accordingly, out of all the situations in which we had 7 simultaneous outliers, we notice that Poland had an outlier in 50% of the cases.

The countries that tend to have isolated outliers were those countries for which we see big numbers in the left side of the table and relatively small numbers in the right side of the table. Slovenia is the only one with such a situation. However, the vast majority of the countries tend to show a higher proportion of outliers that were happening in the same time. This is important evidence on stable co-movement of the European stock markets, showing that relevant information has the power to provide important shocks at a regional level.

The next step was to compute dynamic conditional correlations using the GARCH specification mentioned in the previous section. The means of the correlations for each pair are produced in the following table.

	Germany	France	UK	Spain	Switzerland	Italy	Portugal
Germany							
France	0.86						
UK	0.78	0.79					
Spain	0.70	0.77	0.68				
Switzerland	0.74	0.72	0.70	0.64			
Italy	0.75	0.81	0.71	0.78	0.66		
Portugal	0.50	0.54	0.51	0.57	0.49	0.54	
Ireland	0.34	0.34	0.33	0.29	0.29	0.31	0.27

Austria	0.44	0.42	0.43	0.40	0.41	0.43	0.38
Poland	0.50	0.45	0.45	0.40	0.40	0.41	0.35
Czech Republic	0.41	0.40	0.39	0.35	0.34	0.37	0.34
Hungary	0.31	0.29	0.31	0.24	0.27	0.25	0.26
Romania	0.10	0.00	0.10	-0.70	0.07	0.08	0.04
Slovenia	0.00	0.00	0.01	0.01	0.03	-0.01	-0.02

	Ireland	Austria	Poland	Czech Republic	Hungary	Romania	Slovenia
Germany							
France							
UK							
Spain							
Switzerland							
Italy							
Portugal							
Ireland							
Austria	0.26						
Poland	0.18	0.33					
Czech Republic	0.22	0.48	0.33				
Hungary	0.18	0.24	0.28	0.27			
Romania	0.04	0.14	0.05	0.07	0.08		
Slovenia	-0.02	0.02	0.02	0.02	-0.03	-0.01	

Table 3: The mean values of the correlations computed with the DCC model for five-minute returns

We can notice that the higher values of the correlations are present in the upper part of the table, which means that the index returns tend to be correlated mostly among the developed countries and less correlated with the Eastern European ones. The latter also show that they are not so much correlated neither among themselves, which is evidence of their particular independence on the Western European stock markets.

The next analysis in our work dealt with the construction of a VAR for the volatilities of the stock index returns. Due to lack of space, the final results of the estimation are not provided here but we mention that we estimated a VAR up to the second lag for all the series in our database. Only very few coefficients proved to be significant: DAX, CAC, UKX, SMI and FTSEMIB seem to be dependent on the first lag of WIG, PSI20 is dependent on the second lag of DAX and the second lag of WIG, ATX is dependent on the first lag of SMI, WIG is dependent on the first lag of DAX and BUX is dependent on the second lag of FTSEMIB and its first lag.

The last part of our analysis consisted in the calibration of the Maheu and McCurdy (2007). Our aim was to find the coefficients for each of the returns in our sample, and then to analyze the parameters of the jump densities by comparing them among the returns in our database. Thus, the jump densities were introduced into another VAR analysis and we tried to see if the densities are providing any kind of dependence. We are not providing here the results, but we mention that the estimation did not provide any significant parameters.

5 Conclusions

This paper uses high frequency stock market index returns to check for the co-movements in the European region. Using 14 indexes for a period of about one year, the common dynamics of the five-minute returns were analyzed using many tools: the properties of the distributions of each series, the jumps defined as outliers of the 95% confidence interval and their simultaneity, the dynamics of the correlations, the relationships among volatilities and then the relationships among the densities for a jump-diffusion model.

This study revealed the fact that there is significant dependence of the returns on the movement of the other returns in the sample, especially when we took into account the extreme values. These “jumps” tend to be simultaneous at the regional level and they are evidence of the fact that the information is spread fast at the European capital markets.

6 References

Andersen, T. G., Benzoni, L. & Lund, J. (2002).An empirical investigation ofcontinuous-time equity return models.*Journal of Finance*, no. 62, pp. 1239–1284.

Barry, C. B., Peavy III, J. W. & Rodriguez, M. (1998).Performance Characteristics of Emerging Capital Markets.*Financial Analysts Journal*, vol. 54, no. 1, pp. 72-80.

Beine, M. &Candelon, B. (2011).Liberalisation and stock market co-movement betweenemerging economies. *Quantitative Finance*. Vol. 11, no. 2, pp. 299-312.

Bekaert, G., Erb, C. B., Harvey, C. R. &Viskanta, T.E. (1998). Distributional Characteristics of Emerging Market Returns and Allocation.*Journal of Portfolio Management*, vol. 24, no. 2, pp. 102-116.

Brooks, R., Del Negro, M. (2004). The rise in comovement across national stock markets: market integration or IT bubble?.*Journal of Empirical Finance,* no. 11, pp.659–680.

Brooks, R., Del Negro, M. (2005). Country versus region effects in international stock returns. *Journal of Portfolio Management*, pp. 67–72,Summer, 2005.

Brooks, R., Del Negro, M. (2006).Firm-level evidence on international stock market comovement.*Review of Finance*, no. 10, pp. 69–98.

Candelon, B., Piplack, J., Straetmans, S. (2008). On measuring synchronization of bulls and bears: the case of East Asia.*Journal of Banking and Finance*, no. 32, pp. 1022–1035.

Chernov, M., Gallant, R. A., Ghysels, E. &Tauchen, G. (2003).Alternative models forstock price dynamics. *Journal of Econometrics*, no. 116, pp. 225–257.

Chib, S., Nardari, F. &Shephard, N. (2002).Markov chain Monte Carlo methods for stochastic volatility models, *Journal of Econometrics*, no. 108, pp. 281–316.

Didier, T., Love, I., &Peria, M. S. M. (2010).What Explains Stock Markets’ Vulnerabilityto the 2007–2008 Crisis?.*The World Bank Policy Research Working Paper* 5224

Divecha, A.B., Drach, J. &Stefek, D.(1992).Emerging Markets: A Quantitative Perspective.*Journal of Portfolio Management*, 19, 1, pp. 41-50.

Eraker, B., Johannes, M. S. & Polson, N. G. (2003).The impact of jumps in volatilityand returns, *Journal of Finance*, vol. 58, no. 3, pp. 1269–1300.

Forbes, K., Rigobon, R.(2002). No contagion, only interdependence: measuring stock market comovements. *Journal of Finance*, no. 57, pp. 2223–2261.

Grubel, H.(1968). Internationally diversified portfolios: welfare gains and capital flows.*American Economic Review*, vol. 58, no. 5, pp. 01299–1314.

Harrison B., Lupu, R. &Lupu, I. (2010), Statistical Properties of the CEE Stock Market Dynamics.A Panel Data Analysis.*The Romanian Economic Journal*, Year XIII, no. 37, pp. 41-54.

Harrison, B. & Moore, W. (2009).Stock Market Comovement in the European Union andTransition Countries.*Financial Studies*, vol. 13, no. 3, pp. 124-151.

Harvey, C.R (1995). Predictable Risk and Returns in Emerging Markets.*Review of Financial Studies*, vol. 8, no. 3, pp. 773-816.

Horobet, A. &Lupu, R. (2009). Are Capital Markets Integrated? A Test of Information Transmission within the European Union.*Romanian Journal of Forecasting*, no.2, Vol. 10.

Jorion, P. (1988). On jump processes in the foreign exchange and stock markets.*Review of Financial Studies*, vol. 1, no. 4, pp. 427–445.

Karolyi, G.A., Stulz, R.M. (1996). Why do markets move together? An investigation of U.S.–Japan stock returncomovements.*Journal of Finance*, vol. 51, no. 3, pp. 951–986.

King, M., Sentana, E., Sushil, W. (1994). Volatility and links between national stock markets. *Econometrica*, vol. 62, no. 4, pp. 901–933.

King, M., Wadhwani, S. (1990).Transmission of volatility between stock markets.*Review of Financial Studies*, vol. 3, no. 1, pp. 5–33.

Kizys, R., Pierdzioch, C.(2009). Changes in the international comovement of stock returns and asymmetric macroeconomic shocks. *Journal of International Financial Markets*, Institutions and Money, vol. 19, no. 2, pp. 289–305.

Lin, W.-L., Engle, R. F. & Ito, T. (1994).Do Bulls and Bears Move Across Borders? International Transmission of Stock Returns andVolatility, *The Review of Financial Studies*, vol. 7, no. 3, pp. 507-538.

Lin,W.-L., Engle, R., Ito, T. (1994). Do bulls and bears move across borders? International transmission of stock returns and volatility.*Review of Financial Studies*, vol. 7, no. 3, pp. 507–538.

Longin, F., Solnik, B. (1995). Is the correlation in international equity returns constant: 1960–1990?.*Journal of International Money and Finance*, vo. 14.no. 1, pp. 3–26.

Longin, F., Solnik, B. (2001).Extreme correlation of international equity markets.*Journal of Finance*,vol. 56, no. 2, pp. 649–676.

Lupu, R. &Lupu, I. (2009). Contagion across Central and Eastern European Stock Markets: A Dynamic Conditional Correlation Test.*Economic Computation and Economic Cybernetics Studies and Research*, Vol. 43, No. 4, pp. 173-186.

Maheu, J. M. & McCurdy, T. H. (2004). News arrival, jump dynamics, and volatilitycomponents for individual stock returns.*Journal of Finance*, vol. 59, no. 2.

Maheu, J. M. & McCurdy, T. H. (2007).Modeling foreign exchange rates with jumps.*Working Papers* tecipa-279, University of Toronto, Department of Economics.

Morana, C. &Beltratti, A. (2008).Comovements in International Stock Markets.*Journal of International Financial Markets, Institutions and Money*, vol. 18, no. 1, pp. 31-4.

Pajuste, A. (2002). Corporate Governance and Stock Market Performance in Central and Eastern Europe: A Study of Nine Countries',*Stockholm School of Economics*. Working paper, Available at SSRN: http://ssrn.com/abstract=310419 or doi:10.2139/ssrn.310419

Rua, A. & Nunes, l. C. (2009). International comovement of stock market returns: A wavelet analysis. *Journal of Empirical Finance*, no. 16, pp. 632–639.

Soydemir, G. (2000). International Transmission Mechanismof Stock Market Movements: Evidencefrom Emerging Equity Markets. *Journal of Forecasting*, no. 19, pp. 149-176.