3.

SIMULTANEITY OF TAIL EVENTS FOR DYNAMIC CONDITIONAL DISTRIBUTIONS OF STOCK MARKET INDEX RETURNS

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Abstract

The tail events represent a phenomenon long studied in the literature of stock market returns. The dynamical properties of conditional distributions are currently analyzed by means of the first four moments via Gram-Charlier likelihood functions. We propose an analysis of changes in the values of means, volatilities, skewness and kurtosis coefficients for a series of intra-daily frequency of 14 stock market returns to develop a jump detection mechanism based on the estimation of a dynamic threshold that relies on the first four moments of the distribution. Our main objective consists in the estimation of simultaneity of tail values for these moments. We consider the 5% up and 5% down event as jumps in the series of these coefficients and we compare their realizations across the series of different stock markets for simultaneity. Finally we propose an indicator that can show the degree of co-movements in the extreme values of these coefficients for different frequencies.

Keywords: simultaneity indicator, dynamic threshold for jump detection, dynamic skewness and kurtosis, Gram-Charlier likelihood, stock market comovements, extreme events

JEL Classification: C12, C51, G17

I. Introduction

The idea of tail events generated a wide stream of research in the field of capital markets due to the effect that it has for risk management and capital adequacy measures. The main objective is to build an indicator that takes into account the simultaneity of outliers in the series of stock market returns computed for high frequencies and for higher moments of the distribution.

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We use (A. Gabrielsen, 2012) to build dynamic skewness and kurtosis coefficients via the proposed Gram-Charlier likelihood function applied on the errors of a simple GARCH(1,1) model for the series of returns.

The objective is to analyze the impact of extreme events on the dynamics of the conditional distribution and to understand their propagation at the international level on the stock markets. Looking at different frequencies we also aim at understanding the way in which the extreme values are preserved from the high frequency to the low frequency, which could be understood as a measure of their severity. One of the stylized facts of stock market returns refers to convergence to normality when looking at distributions for lower frequencies, due to compensations that have the tendency to cancel part of the extremes. This phenomenon has the effect of losing the specificities of stock market dynamics when looking at lower frequencies and therefore it would be important to understand the way in which normality wipes the jags out. We try to investigate these properties of the dynamics of stock market returns by looking at the indicator of simultaneity of extreme events for different frequencies.

II. Literature Review

The phenomenon of co-movements or co-dynamics is studied in the field of international finance mostly from the appearance of the concept of contagion, which deals with the existence of high correlations when returns are negative and they persist in the left tail of the distribution. A long stream of research first dealt with the computation of simple correlations and the effect of the materialization of some sovereign debt crises (Latin America and later the Asian Crisis) and then moved into more complex modeling using different members of the GARCH family of dynamic conditional correlations and non-linear measures of the dependence (like copulas).

A series of empirical evidence was generated by the analysis of simple correlations between national stock market index returns. Among the first observations lies the finding that the linear dependence between index returns tend to change in time, as evidenced by S. G. Makridakis (1974) and J. Knif (1999). Another analysis of this kind dealt with the observations that correlations tend to be larger when an increase in the intensity of economic integration is acknowledged, as evidenced by F. Longin (1995) and W. N. Goetzmann (2005). In the analysis of this kind of dependence initial studies tended to provide support for the international portfolio diversification benefits as they succeeded to prove that correlations have favorable dynamics (it is the case of F. Longin, 1995, A. Ang, 2002 and F. Longin, 2001). However, one important feature of linear dependence that also became a “stylized fact” due to large-scale evidence, contends that correlations tend to increase when prices are falling and tend to have reduced values during market development – the so-called phenomenon of contagion. The first studies in this field were M. King (1990), F. Chesnay (2001) and Baele (2005).

Many techniques used for the measurement of dependence were employed by numerous studies in the field of international co-dynamics. We provide a series of papers that approach this topic. Hence, the problem of dynamic common trends is analyzed by P. Christoffersen (2005) in an evaluation of the error of estimation in the case of risk measurement using Value-at-Risk estimates and Expected Shortfall forecasts.

An important stream of research has been motivated by the analysis of jumps in the values of returns. The existence of extreme values and the appropriateness of jump-diffusion in the characterization of stock market returns dynamics attracted researches toward the calibration of sophisticated models that also permitted for autoregressive volatility. Among others we mention Jorion (1988), T. G. Andersen (2002), S. Chib (2002), M. Chernov (2003), B. Eraker (2003), J. M. Maheu (2004). One important reference is J. M. Maheu (2007), who used models that allow for jumps to capture the phenomenon of volatility persistence as well as the non-normal values for the skewness and kurtosis coefficients of returns. The empirical evidence show also statistical properties of the estimated jumps, which have to change in size as well as in the variance of their size. Such market reactions are motivated by the fact that releases of macroeconomic figures are changing the overall equilibrium in the markets, as shown in Albu *et al*. (2014a) and Albu *et al*. (2014b) that make reference to the response of high frequency log-returns to macroeconomic events.

M. Acatrinei (2011) used high frequency stock market returns to estimate a jump-diffusion model as well as a stochastic volatility model to construct a comprehensive model in which the two models are weighted in keeping with the forecast performance in an out-of-sample measurement. The analysis recommends techniques to choose the best model for risk measurement reasons.

The Central and Eastern European stock markets are also analyzed in a series of papers that focused on the analysis of their correlations with the developed markets from EU. The evidence that these types of dependences are increasing is founded on the conjecture that these countries will meet financial integration generated by the quality of holding EU membership.

S. Claessens (2002) deals with the study of the development of capital markets in Central and Eastern Europe and the conclusion of this analysis supports the idea of future consolidation and an increased correlation with the developed stock markets in Western Europe. However, the relations of these markets with the other European stock markets are not the same in the CEE group. Pajuste (2002) noticed that countries like the Czech Republic, Hungary and Poland usually show more dependence with the EU market, while Romania and Slovenia have lower correlations that sometimes are also negative.

The same results is confirmed by Chelley-Steeley (2005) in a study of the phenomenon of segmentation for the stock markets in Central and Eastern Europe. The process of integration is evidenced to have larger effects in the case of Poland and Hungary, while the segmentation is strongly acknowledged in the case of the Russian equity market overall.

R. Lupu (2011) studies the dynamics of the correlations of the high frequency stock index returns in pursuit of the same idea of simultaneity of the outliers found for the series of these correlations. The paper computes various forms of correlations that allow for stylized facts of stock market returns (as the heteroskedasticity effect) for many frequencies and provides evidence in support of the phenomenon of contagion.

Our paper aims to provide an analysis of the simultaneity phenomena present in the dynamics of stock market returns. In order for this objective to be attained we develop a semi-parametric jump detection mechanism that relies on the dynamic characterization of the empirical distribution of stock market returns by estimating the first four moments of this distribution. These four moments allow us to determine a dynamic threshold for any definition of tails and help us to identify these extreme events. Once the jumps were determined, we define a statistical indicator to measure the simultaneity both as a characterization for the whole sample and in a dynamic perspective, for each week in our sample.

III. 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), BEL20 (Belgium), ISEQ (Ireland), ATX (Austria), WIG20 (Poland), PX (Czech Republic), BUX (Hungary), ASE (Greece) and BET (Romania). The period we took into account was from the 18th of June 2014 until the 9th of October 2014.

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 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.

Table 1

The Statistical Properties of the Common Sample of Returns

	Mean	Standard deviation	Skewness	Kurtosis
Germany	-0.00001	0.00077	0.14237	7.87179
France	-0.00002	0.00078	-0.10602	11.09308
UK	-0.00002	0.00062	-0.39821	8.40659
Spain	-0.00001	0.00093	0.20480	8.89149
Switzerland	-0.00001	0.00051	-0.11631	5.86954
Italy	-0.00003	0.00112	0.05581	7.75467
Portugal	-0.00004	0.00110	-0.87121	20.37638
Ireland	-0.00002	0.00064	0.04029	5.76079
Austria	-0.00003	0.00082	-0.19005	8.18463
Poland	-0.00001	0.00073	-0.26303	7.63933
Czech Republic	-0.00001	0.00089	-0.18421	10.43079
Hungary	-0.00002	0.00100	-0.09262	6.97274
Belgium	-0.00001	0.00056	-0.00310	7.85924
Greece	-0.00004	0.00142	-0.12889	5.36219
Romania	0.00002	0.00400	6.99675	594.93665

We notice that the series of stock market returns tend to comply with the known stylized facts considered in standard approaches like Christoffersen (2003) are met for the high frequency returns too. The non-normality, recognized by the existence of (usually) negative skewness and excess kurtosis is found for the data we work with.

The use of high frequency data involves problems related to regular dynamics inside trading sessions. These dynamics, already a stylized fact identified in a series of papers (we mention here the work of Andersen and Bollerslev, 1997, Andersen and Bollerslev, 1998, Boudt, Croux and Laurent, 2011, and Erdemlioglu, Laurent and Neely, 2013, among others) exhibit periodicities, which have to be taken into account at the intra-day analysis.

In order to be able to perform the analysis that follow in the paper, we decided to use the Boudt, Croux and Laurent (2011) methodology to adjust the log-returns with their periodicities. According to their specification, the *Integrated Variance* is *w(z)* = $\begin{cases} 1 \text{ if } z \leq 6.635 \\ 0 \text{ else.} \end{cases}$, which represents the so-called *hard rejection function* and *d* comes from $d_{t,i} = \left(\frac{R_{t,j}}{\hat{\sigma}_{t,j}}\right)^2$, the robustly standardized return (return scaled by its standard deviation).

The periodicity paradigm for the computation of jumps assumes that $\sigma_{t,j}^2 = s_{t,j} f_{t,j}$, where $s_{t,j}$ is the stochastic part of the intra-daily volatility that is assumed to be constant over the day but varies from one day to another. Here we use $s_{t,j}$ = standard deviation of realized returns and $f_{t,j}$ is the standard deviation periodicity, i.e. $\hat{f}_{t,j}^{SD} = \frac{SD_{t,j}}{\sqrt{\frac{1}{m}\sum_{j=1}^{m} SD_{t,j}^2}}$, i.e. a standard deviation adjusted with the estimated periodicity. The log-returns to be used in the next analysis are therefore periodicity-adjusted returns, i.e. returns divided by the $f_{t,j}$ measure of periodicity.

The first step in our analysis consisted in the development of the jump identification technique based on the dynamic threshold of the conditional empirical distribution. We will characterize this distribution by using the central moments in a Gram-Charlier expansion, i.e. the determination the variance, skewness and kurtosis coefficients for each moment in time (i.e. at the 5-minute frequency). The methodology used for this estimation follows the lines of A. Gabrielsen (2012) by maximizing the Gram-Charlier likelihood function across all the series and then inside each week from the sample of stock returns used for this analysis. However, instead of a RiskMetrics model, we use a heteroskedastic conditional rule as in a GARCH(1,1) model for the dynamics of all the three moments of the conditional distribution. Therefore, our model is:

$$\sigma_t^2 = \alpha_{0,\sigma} + \alpha_{1,\sigma}\sigma_{t-1}^2 + \alpha_{2,\sigma}R_{t-1}^2 \tag{1}$$

$$sk_t = \alpha_{0,sk} + \alpha_{1,sk}sk_{t-1} + \alpha_{2,sk}R_{t-1}^3 \tag{2}$$

$$ku_t = \alpha_{0,ku} + \alpha_{1,ku}ku_{t-1} + \alpha_{2,sk}R_{t-1}^4 \tag{3}$$

where R_t is the log-return at moment *t*, σ_t^2 is the variance at moment *t*, sk_t is the skewness at moment *t* and ku_t is the kurtosis at moment *t*. The system of equations describes the dynamics of the three moments of the conditional distribution, specifying the relationships that they are supposed to have with the immediate past.

For equation (1), the estimation of the parameters is realized according to the standard GARCH (1,1) specification. The

The estimation of $a_{i,m}$ parameters (where $i = 0,1,2$ and $m = sk, ku$) will be realized using the Gram-Charlier density presented in A. Gabrielsen (2012) for a model that describes a RiskMetrics dynamics. In close keeping with those lines, the density is defined as:

$$f(R_t) = \frac{\phi(R_t)g^2(R_t)}{h(R_t)} \tag{4}$$

where: $\phi(R_t)$ is the standard normal distribution and

$$g(R_t) = 1 + \frac{sk_t}{6}\left(R_t^3 - 3R_t\right) + \frac{ku_t - 3}{24}\left(R_t^4 - 6R_t^2 + 3\right) \tag{5}$$

$$h(R_t) = 1 + \frac{sk_t^2}{3!} + \frac{(ku_t - 3)^2}{4!} \tag{6}$$

Therefore, the log-likelihood function for one observation can be written as

$$l_t = -\frac{1}{2}log(2\pi) - \frac{1}{2}log(\sigma_t^2) - \frac{1}{2}R_t^2 + log[g^2(R_t)] - log[h(R_t)] \tag{7}$$

The above mentioned likelihood function was used for the estimation of parameters in relations (2) and (3) for a series of random variables that are standardized using the parameters previously obtained through estimation of relation (1). Therefore the estimation of the parameters is performed in two steps: first the estimation of coefficients in relation (1) and then the estimation of coefficients in relations (2) and (3).

The parameters are estimated[2] first for the whole common series of 5-minute returns (consisting in 4544 observations) and next in a dynamic manner, for rolling windows of 1000 observations[3].

In order to build an analysis concerning the measurement of common realizations of extreme returns as proof of a contagion phenomenon we considered the following steps:

1) We chose a value for the measurement of thresholds, the exceeding of which could be considered as a “tail event”, and we compute the upper and lower values for the

[2] The estimation process was performed in Matlab by construction of a function and use of the built-in optimization engine in a routine that can be made available upon request. The model estimation for the relation (1) was performed using the built-in function of Matlab.

[3] The model we used is a dynamic conditional model with a specification similar to a GARCH(1,1) model. The sample size of the rolling window was considered as optimal if it lies between 700 and 1000 observations in Ng and Lam (2006) and 1000 is considered a relative small sample in Matei (2009).

10% up and down of the distribution. This represents the implementation of the jump-detection mechanism developed here;

2) We find the jumps and save the moments when they were realized as well as their average size;

3) We identify the common jumps, i.e. realizations of jumps in the same time across the 15 series of stock market returns;

4) We build an indicator of this simultaneity.

The first step consisted in the use of the Cornish-Fisher formula for 10% probability in case of the lower tail threshold and 90% probability in case of the upper tail threshold. The formula used was

$$CF^{-1}(p) = \Phi_p^{-1} + \frac{sk}{6}\left(\left(\Phi_p^{-1}\right)^2 - 1\right) + \frac{ku}{24}\left(\left(\Phi_p^{-1}\right)^3 - 3\Phi_p^{-1}\right) - \frac{sk^2}{36}\left(2\left(\Phi_p^{-1}\right)^3 - 5\Phi_p^{-1}\right) \quad (8)$$

where: p is the probability used for the computation of the tail separator (in our case 10% and 90%), sk is the skewness coefficient, ku is the kurtosis coefficient, and Φ_p^{-1} is the inverse standard normal distribution for the probability p. This approach will help us to determine the thresholds and the values used for the skewness and kurtosis coefficients are the mean values of these coefficients for the whole sample of returns for which we need to compute the simultaneity coefficients, i.e. the whole sample and each week.

After steps 2) and 3) we computed the indicator of simultaneity both for the whole sample and all the countries, as a measurement of simultaneity for all the series of stock returns on one hand, and for each country separately, both for the whole sample and for each week, on the other hand.

The indicator computed for the whole sample takes the following form:

$$I = \frac{\sum_{j=1}^{14} jumps_{tail} \times \frac{nj_{tail}}{Nj_{tail}}}{14} \quad (9)$$

where j counts the countries, $jumps_{tail}$ is the number of common jumps that can be obtained, and it takes the values 1…14, where 14 is the number of countries in our sample, $tail$ can be up (u) or down (d), corresponding to the lower tail jumps and upper tail jumps , nj_{tail} is the number of situations in which we recorded a number of common jumps equal to $jumps_{tail}$, Nj_{tail} is the total number of situations in which we acknowledged at least two jumps happening simultaneously. Therefore, computed in this way, the indicator *I* represents a measurement of how much simultaneity we can acknowledge in the tails for the whole sample. In absolute terms, is takes values between 0 and 1. For instance, in case there are only individual jumps, i.e. none of the jumps identified in the respective time frame was simultaneous across countries, but the algorithm succeeded to detect some jumps, then the value of *I* indicator is 1/14. It will have a value of 0 in case no jumps were detected and a value of 1 in case all the detected jumps happened in the same time across all countries. The value of 1 would represent perfect simultaneity; the value of 1/14 stands for perfect independence across countries, while the value of 0 reflects the situation when no jumps were detected.

This indicator was computed for the whole sample and for all countries and also for each week, determining a measurement of the dynamics of the simultaneity phenomenon for the stock markets in our analysis.

For each country in the sample, we also computed the simultaneity indicator using the following form:

$$I_c = \frac{\sum_{j=1}^{14} jumps_{tail} \times \frac{nj_{tail,c}}{Nj_{tail,c}}}{14} \tag{10}$$

where: $nj_{tail,c}$ represents the number of situations in which we observed a number of common jumps equal to to $jumps_{tail}$, $Nj_{tail,c}$ is the total number of situations in which we acknowledged at least two jumps happening simultaneously for the country *c*. The computation of such indicators allows for the visualization of the dynamics of the simultaneity for all the moments of the distribution at each country.

IV. Results

Results of derived from the recalibration of models (1), (2) and (3) for the weekly series of stock returns can only be produced by presenting the statistics of these parameters. We exhibit in Table 2 (Annex) the mean values of the coefficients across each sample for the 36 rolling windows and on each country. The coefficients for the Romanian stock market seem to be most different from the rest of the group, mostly for the case of the volatility and the skewness dynamics. The persistence coefficient for the kurtosis is rather high, which might determine a nonlinear dependence of the variability of returns on their historical ranges.

Disregarding Romania, which seems to have an outlier behavior, we notice similar values as the one for the whole sample. With these estimates we can also have a better perspective on the dynamics of the estimates of these parameters as we move in time. One such perspective is presented also in Figure 1, where we can see the dynamics of the averages of the coefficients α_2 across all countries but in time for each of the three relations (1), (2) and (3). We can notice that the dependence on the immediate past suffers very small changes as we move in time for the sample of returns in our analysis.

Table 3 and 4 (Annex) provide about the number of jumps happening in the lower tail of the conditional distribution for the series of returns, volatilities, skewness coefficients and kurtosis coefficients computed via Gram-Charlier likelihood estimations. We notice that usually there are large numbers of common tail situations for the lower-tail jumps and, which provide proof to the fact that, on average, a situation with extreme value for the higher order moments of the distribution at a certain moment in time is accompanied by the same situation at the European level, i.e. in many stock markets. Visually, we can notice that the situations with common jumps are quite common among the stock markets, at the 5-minute frequency, which can be considered as proof of efficient communication among these markets.

Figure 1

The Dynamics of the α_2 Coefficient for the Variance Estimated Using the Rolling Window for 36 Subsamples of 1000 Observations

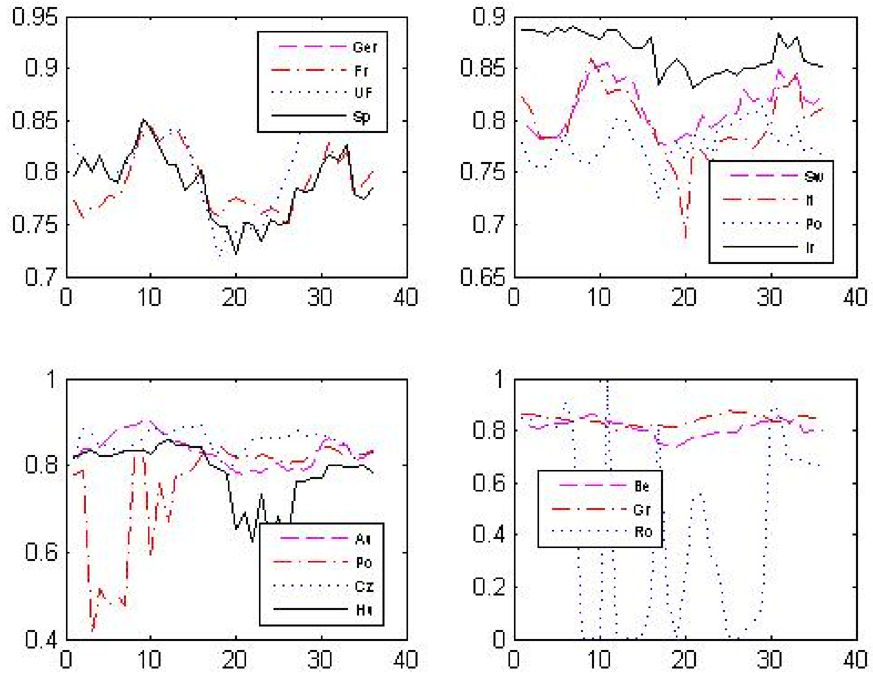
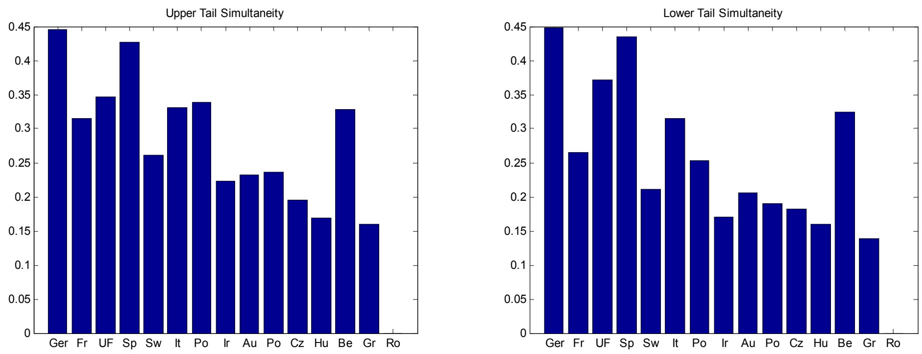


Figure 2

The Values of the Simultaneity Indicator for Each Country for the Upper Tail (Left) and Lower Tail (Right)

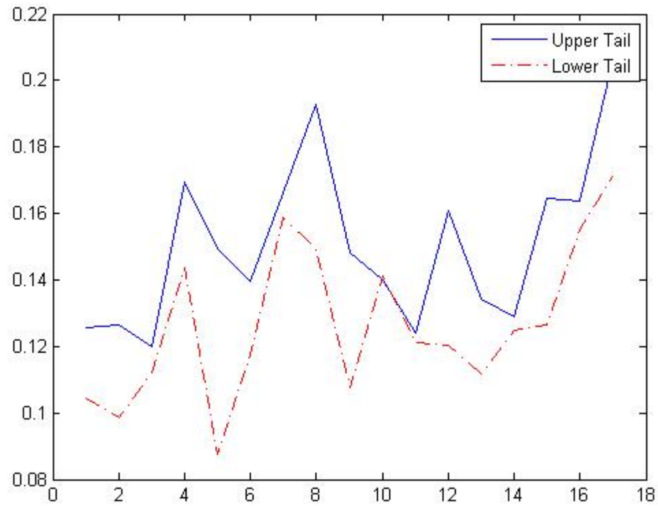


The table was replicated for the situation of up jumps, by taking into account the Cornish-Fisher threshold for the upper tail of the distribution for the whole sample. The upper tail jumps showed similar simultaneity as the lower tail ones and the jumps for each week provided information about the changes in the so called simultaneity. More information can be obtained by inspection of the simultaneity indicator that was built as explained in the previous section.

Figure 2 shows the values of the indicator computed for each country. We notice the fact that Romania does not show any simultaneity with the other national stock markets. The largest values are obtained for Germany and France, which means that they are the countries mostly connected with the rest of the capital markets.

Figure 3

The Dynamics of the Simultaneity Indicator across the 17 Weeks in Our Sample



We notice that the indicator of simultaneity tends to be approximately in the same range of values across the weeks in our sample and the indicator for the upper tail seems to have similar values as the ones for the lower tail, which acknowledges the existence of symmetrical simultaneity.

V. Conclusions

The phenomenon of stock market co-dynamics has been analyzed in many studies in the field of international finance. The transmission of information across countries was studied mostly in the situations of financial crises in search for evidence on contagion, acknowledged as increased correlation when returns become large and negative. However, this phenomenon, captured with various techniques that measure the linear and simple non-linear dependence, was not investigated a lot in the tails of the distribution. The existence of this kind of dependence influences the management of international portfolios as well as the risk management at the international level.

This paper contributes to the identification of dependence by using high frequency returns for a sample of 15 national stock markets and on one hand proposes a new extreme values detection mechanism that relies on the dynamic estimation of the central moments of the empirical distribution of stock returns and on the other hand a measurement of the non-linear dependence existing among the stock markets in the tails of the distribution.

The Gram-Charlier likelihood functions were used for the computation of skewness and kurtosis coefficients of the conditional distributions of returns at each moment in time. Their dynamics were analyzed for situation of extremes computed considering a measurement of the quintiles for 10% up and 10% of the distributions. The quintiles were computed using the Cornish-Fisher function where for the values for skewness and kurtosis the averages of the series of estimated higher order coefficients were used.

The results show a high level of dependence in the tails both at the level of returns as well as in the case of the higher order moments.

The paper also proposes a new measurement of dependence by using an indicator for the simultaneity of tail events at the level of the 15 national stock markets used in the analysis. The indicator is computed for the whole sample as well as for each country and for each week in the sample. This indicator may produce a possible way to account for extreme events and it may be important for reasons related to portfolio management and capital adequacy.

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Table 2

Coefficients Estimated for the Relations (1), (2) and (3) for the 5-Minute Returns Presented as Averages across the 36 Rolling Windows

	Germany	France	UK	Spain	Switzerland	Italy	Portugal	Ireland	Austria	Poland	Czech Republic	Hungary	Belgium	Greece	Romania
$\alpha_{0,\sigma}$	5.8E-08	5.8E-08	3.6E-08	8.5E-08	2.5E-08	1.3E-07	1.2E-07	3.9E-08	6.7E-08	6.4E-08	7.9E-08	1.1E-07	3.1E-08	1.9E-07	1.2E-05
$\alpha_{1,\sigma}$	0.7884	0.7915	0.8127	0.8028	0.8122	0.7977	0.7771	0.8657	0.8331	0.7581	0.8547	0.7836	0.8115	0.8417	0.4280
$\alpha_{2,\sigma}$	0.1165	0.1146	0.0933	0.1009	0.0908	0.1018	0.1335	0.0345	0.0670	0.1300	0.0450	0.1105	0.0909	0.0628	0.0666
$\alpha_{0,sk}$	-0.0854	-0.0851	-0.0909	-0.2599	-0.1373	-0.2339	-0.1832	-0.2262	-0.0979	-0.1400	-0.2152	-0.3096	-0.1932	-0.3128	-0.0220
$\alpha_{1,sk}$	0.7222	0.7369	0.8000	0.6312	0.7046	0.6828	0.6721	0.7018	0.8161	0.7871	0.6346	0.7700	0.7698	0.6181	0.2124
$\alpha_{2,sk}$	0.3174	0.2710	0.2075	0.1587	0.2358	0.2610	0.2131	0.2498	0.1927	0.2294	0.2910	0.2733	0.2323	0.2434	0.2831
$\alpha_{0,ku}$	0.4424	0.3574	0.5437	0.6481	0.4840	0.4891	0.5442	0.4927	0.2946	0.2867	0.7897	0.6172	0.4125	0.6179	0.1657
$\alpha_{1,ku}$	0.6830	0.6969	0.6959	0.7048	0.7026	0.7012	0.6773	0.7293	0.7314	0.6657	0.6312	0.6487	0.6789	0.6307	0.9024
$\alpha_{2,ku}$	0.1334	0.0907	0.1080	0.0798	0.0956	0.1196	0.1649	0.1121	0.1165	0.1567	0.1454	0.1513	0.1404	0.1126	1.0276

Table 3

Up Jumps for the Whole Series of Returns, Computed Using the Cornish-Fisher Threshold at 10%

No. of common jumps	Germany	France	UK	Spain	Switzerland	Italy	Portugal	Ireland	Austria	Poland	Czech Republic	Hungary	Belgium	Greece	Romania
1	0	44	27	7	110	45	16	158	187	98	135	177	38	256	0
2	10	80	45	12	127	57	10	126	163	81	109	150	65	155	0
3	17	105	44	19	70	52	7	85	104	53	49	51	74	59	0
4	22	84	44	22	51	53	5	37	55	28	25	19	61	26	0
5	21	68	33	22	34	36	6	31	42	23	18	17	50	19	0
6	33	57	32	21	29	31	2	25	35	15	11	11	47	11	0
7	39	54	36	31	38	44	5	26	33	13	16	12	44	8	0
8	25	31	25	22	25	31	5	13	27	11	7	2	29	3	0
9	27	31	28	24	24	28	4	19	25	12	11	5	31	10	0
10	13	14	13	14	13	13	5	10	13	9	3	2	14	4	0
11	8	8	5	8	7	8	2	6	7	6	3	6	8	6	0
12	2	2	2	2	2	2	1	2	2	1	1	2	2	1	0
13	5	5	5	5	5	5	4	4	5	5	4	4	5	4	0
14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Table 4

Down Jumps for the Whole Series of Returns, Computed Using the Cornish-Fisher Threshold at 10%

No. of common jumps	Germany	France	UK	Spain	Switzerland	Italy	Portugal	Ireland	Austria	Poland	Czech Republic	Hungary	Belgium	Greece	Romania
1	1	48	10	0	151	15	4	222	142	90	81	106	14	291	0
2	1	81	15	2	100	38	5	157	102	71	47	60	29	130	0
3	3	69	8	1	56	25	4	57	62	26	25	27	29	52	0
4	9	57	9	15	48	27	2	33	40	14	11	12	38	21	0
5	11	47	19	7	33	24	2	23	31	9	6	3	33	12	0
6	11	28	12	5	21	16	0	13	20	13	7	7	23	10	0
7	19	31	20	7	25	22	0	17	22	12	4	7	27	11	0
8	8	11	9	4	10	11	0	9	6	4	2	1	10	3	0
9	11	13	12	7	14	12	1	12	13	6	6	3	12	4	0
10	3	5	5	4	4	5	1	4	4	3	2	2	5	3	0
11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
12	3	3	3	3	3	3	0	2	3	1	3	3	3	3	0
13	1	1	1	1	1	1	1	1	1	1	1	0	1	1	0
14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0