Stock Market Comovements of the Emerging European Stock Market Returns

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Abstract
Using high frequency data for European stock market returns, previous research (Acatrinei et. al. 2011) revealed that the outliers of these returns (computed as returns situated outside of the 95% confidence interval) tend to be simultaneous. This can be considered as support for the hypothesis that the stock markets tend to be correlated at the high frequency level. This paper proposes a modeling of these type of interactions by analyzing the characteristics of the dynamic coefficients of correlations between pairs of a series of 14 stock market index returns (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) built in a common sample) computed at the five-minute frequency. The significance of the outliers in the previous studies revealed the fact that one of the properties of the correlation coefficients should be the fat-tail stylized fact, which is also identified for log-returns. As there are many ways to control for this effect in creating a model for stock returns, this paper proposes the use of three types of models to compute the correlations: the GARCH – DCC model, the stochastic volatility model and the jump-process model using a specification presented by Maheu and McCurdy (2007). While for the simple GARCH-DCC model the estimation deals with the maximization of a bivariate normal distribution, for the other two models we use a Bayesian estimation approach, in which the parameters will be discovered by means of Markov Chain Monte Carlo simulation. The calibration will be realized for different frequencies, starting from five-minute and going to daily returns, aiming at capturing the proper frequency for each model, as well as providing a perspective of the time scale structure of the correlations.

Keywords: European stock market returns, GARCH – DCC model, the stochastic volatility model and the jump-process mod
JEL codes: G15, C11, C22

1. Introduction

The Central and Eastern European countries have suffered major shifts in their economic and political systems during their transition period to market economies. The main concern regarding the equity markets of these countries if they have difficulties to produce all benefits for a market economy due to factors like mistrust in their power to attract finance, low liquidity and high volatility, was materialized for some of them, while others succeeded to show important developments in these respects.

The literature evidenced a number of empirical regularities for Emerging European Stock Market: 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.

Using high frequency data for European stock market returns, previous research (Acatrinei et. al. 2011) revealed that the outliers of these returns (computed as returns situated outside of the 95% confidence interval) tend to be simultaneous. This can be considered as support for the hypothesis that the stock markets tend to be correlated at the high frequency level. This paper proposes a modeling of these type of interactions by analysing the characteristics of the dynamic coefficients of correlations between pairs of a series of 14 stock market index returns (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) built in a common sample) computed at the five-minute frequency. The significance of the outliers in the previous studies revealed the fact that one of the properties of the correlation coefficients should be the fat-tail stylized fact, which is also identified for log-returns. As there are many ways to control for this effect in creating a model for stock returns, this paper proposes the use of three types of models to compute the correlations: the GARCH – DCC model, the stochastic volatility model and the jump-process model using a specification presented by Maheu and McCurdy (2007). While for the simple GARCH-DCC model the estimation deals with the maximization of a bivariate normal distribution, for the other two models we use a bayesian estimation approach, in which the parameters will be discovered by means of Markov Chain Monte Carlo simulation. The calibration will be realized for different frequencies, starting from five-minute and going to daily returns, aiming at capturing the proper frequency for each model, as well as providing a perspective of the time scale structure of the correlations.

The remainder of the paper is organized as follows. The next section reviews the literature on capital market comovements. Section III contains a description of our data and methodology. The fourth section presents our empirical results, and is followed by our conclusions in Section V.

2. Literature review

Various findings have emerged in the literature from the study of correlations between international stock markets indices. First, cross-correlations of stock market returns vary over time (Makridakis and Wheelwright, 1974; Knif and Pynnonen, 1999). Second, correlations increase as economic integration intensifies (Longin and Solnik, 1995; Goetzmann et al., 2005) and third, the correlations most likely are higher in bull markets and lower in the bear markets. Among others, Longin and Solnik (1995), Ang and Bekaert (2002), and Longin and Solnik (2001) showed that correlations between markets were going up during the periods of high volatility and correlation coefficients were higher than average when diversification was profitable. Multiple studies rejected the above mentioned third finding and identified that correlations between international stock markets have a tendency to increase when returns decrease (King and Wadhwani, 1990; Chesnay and Jondeau, 2001; Baele, 2005).

Jacquier, Polson and Rossi (1994) developed a new method for inference and prediction in a simple class of stochastic volatility models in witch logarithm of conditional volatility follows an autoregressive time series model. They proposed a new Bayesian approach in which the latent volatility structure is directly exploited to conduct finite-sample inference and calculate predictive distributions. The stochastic volatility parameters were augmented with the time series of volatilities and a Markov chain was constructed in order to draw directly from the joint posterior distribution of the model parameters and unobservable volatilities.

Christoffersen and Goncalves (2005) assess the precision of common dynamic models and quantify the magnitude of the estimation error by constructing confidence intervals around the point VaR and expected shortfall forecasts. The paper suggests a resampling technique which accounts for parameter estimation error in dynamic models of portfolio variance.

Current research has documented the importance of jump dynamics in combination with autoregressive volatility for modeling returns (Jorion, 1988; Andersen et al., 2002; Chib et al., 2002; Eraker et al., 2003; Chernov et al., 2003; Maheu and McCurdy, 2004). Jumps provide an useful addition to stochastic volatility models by explaining occasional, large abrupt moves in financial markets, 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 the conditional distribution of returns using density and variance forecasts. The empirical results indicate that the heterogeneous jump model effectively captures volatility persistence through jump clustering and that the jump-size variance is heteroskedastic and increasing in volatile markets.

Acatrinei et al. (2011) used five-minute frequency for a set of European stock market indexes and build an out-of-sample test for a complex jump process and a stochastic volatility process, both under the specifications of Maheu and McCurdy (2007). They also build a comprehensive model in which the two models hold weights according to their forecast precision and compute its out-of-sample precision. In addition, they approached the idea of co-movements for the stock market indexes and model the whole set using a principal component analysis recomposition of the data using wavelet multiresolution analysis with orthogonal basis. The results provide a method for the selection of the best model for risk measurement reasons.

Emerging markets from Central and Eastern Europe, now members of the European Union and subject of stronger economic links with the developed markets in the EU and between themselves have also drawn the attention of international researchers in more recent years. Expectations are that correlations of CEE markets with the developed markets in EU would grow in time, as long as CEE countries enter into a gradual economic harmonization process requested by EU membership. As consequence, the capital markets of CEE countries would naturally see themselves in a permanent harmonization process, which in turn will lead to a higher integration with the EU capital markets.

Classens et al. (2002) investigate the potential development of CEE capital markets and conclude that their future integration within EU will lead to their consolidation, on one hand, and to increased correlations with EU markets, on the other hand. Pajuste (2002) observes that CEE capital markets differ to a large extent in terms of their correlations with EU capital markets, with Czech Republic, Hungary and Poland displaying higher correlations among them and with the EU market, while Romania and Slovenia demonstrate virtually zero and even small negative correlation with the EU capital market.

This finding is partially confirmed by Chelley-Steeley (2008), who investigates the extent to which the equity markets of Hungary, Poland the Czech Republic and Russia have become less segmented. It was find that in the cases of Poland and Hungary, a significant movement towards market integration has been achieved. However, it is Hungary that is becoming integrated the most rapidly. Also, some reduction in market segmentation is experienced by the Czech Republic but very little movement away from segmentation is exhibited by the Russian equity market overall, although it does appear to experience short bursts of increased integration.

This paper continues previous research performed by Acatrinei, Caraiani and Lupu (2011) and Lupu and Lupu (2011) to characterize the dynamics of the correlations of the high frequency stock index returns and check for the simultaneity of the outliers found for the series of these correlations. In order to make this analysis, the first step consists in the computation of correlations (both using rolling windows and GARCH-DCC approach) for many frequencies and organize the results in such a way that may allow for a characterization of the simultaneity of the outliers in the series of these correlations.

3. Methodology and data

3.1 Modeling conditional covariances

The simplest way to model time varying covariances is to rely on plain rolling averages. For the covariance between asset i and j we can simply estimate:

$$\sigma_{ij,t+1} = \frac{1}{m}\sum_{\tau=1}^{m} R_{i,t+1-\tau} R_{j,t+1-\tau}$$

which is not necessary satisfactory due to the dependence on the choice of *m*.

We can instead consider models with mean-reversion in covariance. For example, a GARCH(1,1) specification for covariance would be:

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

which will tend to revert to its long run average covariance which equals

$$\sigma_{ij} = \omega_{ij} /(1-\alpha-\beta)$$

Until now we not allowed for the persistence parameters to vary across securities in order to guarantee that the portfolio variance will be positive regardless of the portfolio holdings, ω. We will say that a covariance matrix, Σ_{t+1}, is internally consistent if for all vectors ω

$$\omega' \sum_{t+1} \omega \geq 0$$

This corresponds to saying that the covariance matrix is positive-semidefinite. It is ensured by estimating volatilities and covariances in an internally consistent fashion. For example, using a GARCH(1,1) model with α and β identical across variances and covariances will work as well. Unfortunately, it is not clear that the persistence parameters should be the same for all variances and covariance. We therefore now consider methods which are not subject to this restriction.

3.2 Modeling conditional correlations

Because of the restriction on the persistence across variances and covariances and also by the fact that correlations are easily interpreted as they fall in the interval from minus one to one, we model the correlation rather than covariance. Covariances on the other hand are a confluence of correlation and variance. For example, the covariance between two assets could be time-varying even though the correlation is constant simply because the variances are time-varying. Thus in order to truly assess the dynamics in the linear dependence across assets, we need to get a handle on correlation. There is ample empirical evidence that correlations increase during financial turmoil and thereby increase risk even further, therefore, modeling correlation dynamics is crucial to the risk manager.

A simple way to measure correlation is to treat it as the residual from the covariance and the variance models. By definition

$$\sigma_{ij,t+1} = \sigma_{i,t+1}\sigma_{j,t+1}\rho_{ij,t+1}$$

and so

$$\rho_{ij,t+1} = \sigma_{ij,t+1} /(\sigma_{i,t+1}\sigma_{j,t+1}).$$

therefore if for example

$$\sigma^2_{ij,t+1} = \omega + \alpha R_{i,t} R_{j,t} + \beta\sigma^2_{ij,t}, \text{ for all } i, j$$

then

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

which of course is not particularly intuitive. We therefore now consider models where the dynamic correlation is modelled directly. We will again rely on the definition:

$$\sigma_{ij,t+1} = \sigma_{i,t+1}\sigma_{j,t+1}\rho_{ij,t+1}.$$

We can then standardize each return by its dynamic standard deviation to get the standardized returns,

$$z_{i,t+1} = \frac{R_{i,t+1}}{\sigma_{i,t+1}} \text{ for all i.}$$

Notice the conditional covariance of news equals the conditional correlation of the raw returns

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

as $E_t(z^2_{i,t+1}) = E_t(z^2_{2,t+1}) = 1$ from the standardization. Thus modeling the conditional correlation of the raw returns is equivalent to modeling the conditional covariance of the standardized returns.

We can consider GARCH(1,1) type specifications of the form

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

If we rely on correlation targeting, and set $\bar{\rho}_{ij}$ = E [$z_{i,t}z_{j,t}$], then we have

$$q_{ij,t+1} = E\left[z_{i,t} z_{j,t}\right] + \alpha\left(z_{i,t} z_{j,t} - E\left[z_{i,t} z_{j,t}\right]\right) + \beta\left(q_{ij,t} - E\left[z_{i,t} z_{j,t}\right]\right).$$

Again we have to normalize to get the conditional correlations

$$\rho_{ij,t+1} = \frac{q_{ij,t+1}}{\sqrt{q_{ii,t+1} q_{jj,t+1}}}.$$

The key thing to notice about this model is that the correlation persistence parameters α and β are common across i and j. Thus the model implies that the persistence of the correlation between any two assets in the portfolio is the same. It does not, however, imply that the level of the correlations at any time is the same across pairs of assets. The level of correlation is controlled by E [$z_{i,t}z_{j,t}$] and will thus vary over i and j. It does also not imply that the persistence in correlation is the same as the persistence in volatility. The persistence in volatility can vary from asset to asset and it can vary from the persistence in correlation between the assets. But the model does imply that the persistence in correlation is constant across assets.

For the exponential smoother, and for the GARCH(1,1) we can write

$$Q_{t+1} = E\left[z_t z_t'\right](1 - \alpha - \beta) + \beta Q_t.$$

3.2 Data

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.

Table 1: The statistical properties of the common sample of returns

	Mean	Standard deviation	Skewness	Kurtosis
Germany	2.29E-05	0.0010739	0.578152	16.600166
France	1.12E-05	0.0012533	0.496626	12.864755
UK	1.20E-05	0.0009781	0.5941375	14.753085
Spain	1.49E-05	0.0016729	-0.0430855	6.6067927
Switzerland	1.51E-05	0.0008509	-0.0932375	8.5617979
Italy	1.44E-05	0.0014949	0.0801773	9.3638317
Portugal	-2.45E-05	0.001081	-0.1201539	13.080096
Ireland	-5.49E-05	0.0012328	-0.8395642	14.131439

Austria	4.42E-06	0.0009666	0.1104179	8.7922908
Poland	-2.34E-05	0.0007934	-0.0364934	7.618157
Czech Republic	-1.22E-05	0.0009046	0.579411	13.898922
Hungary	-3.63E-05	0.0013338	-0.0609792	10.505096
Romania	5.32E-07	0.0012362	0.2089462	6.9922291
Slovenia	5.13E-05	0.0016394	-1.4016568	29.591791

Source: author's calculations

4. Empirical results

A previous research (Acatrinei, Caraiani, Lupu (2011) and Lupu, Lupu (2011) 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 produce here the same results:

Table 2: The percentage of simultaneous outliers out of all the situations when we experienced outliers in the sample of our stock market index returns

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

Source: Acatrinei, Caraiani, Lupu (2011)

The conclusions of these previous studies showed that only Slovenia showed an isolated 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. We produce here the results of the previous study:

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

	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

Source: Lupu, Lupu (2011)

This result generated the view that the outliers should be important in all the analyses that tends to measure or characterize the co-movements of the returns. As we know there are many ways in which this can be achieved, as we can translate the irregular dynamics into a large kurtosis for the unconditional distribution of returns. We can capture this type of dynamics by using models like the GARCH, the stochastic volatility or the jump-diffusion model. The papers mentioned above provide this kind of analysis but the next extension consists in the analysis of the dynamics of the correlations. As mentioned before, this analysis consists in the computation of the series of correlations of the returns for different frequencies (5-minute, 10-minute, 15-minute, 20-minute, 30-minute, 40-minute and 60-minute returns) for each pair of returns that can be realized using the 14 indices in our sample.

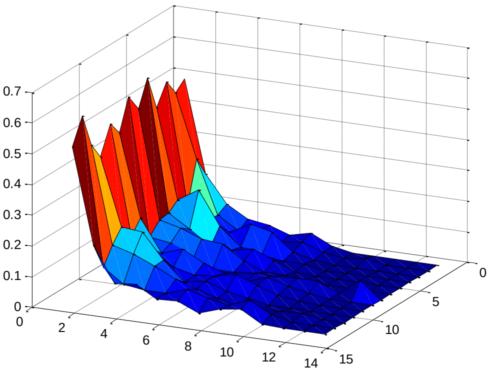
Taking into account the previous analysis, we thought to analyze the dynamics of these series of correlations that are present in the tails of their unconditional distributions. The reason is that, if we manage to understand the tendency in the tails, then maybe we can provide a characterization of the behavior of the dependence by means of simultaneity of outliers.

The first step consisted in the computation of the returns for each of the frequencies mentioned above, having samples that range from 2296 returns (in the case of the 5-minute returns) to 91 returns (in the case of the 60-minute returns). Then we used the data to compute rolling correlations for windows of 100 returns for each frequency. A dynamic matrix of correlations resulted for each frequency, proving 91 possible combinations of pairs of returns, which can be realized with the 14 variables taken into account.

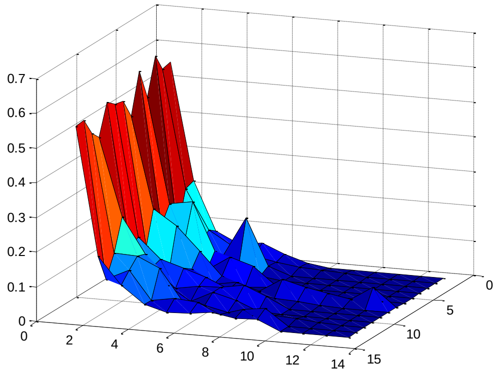
As mentioned, we started with the computation of the outliers, both in the upper and the lower tails. The analysis of the outliers was realized by considering various possibilities of the tails, ranging from 7% to 1%.

Figure 1: Simultaneity of outliers for rolling correlations

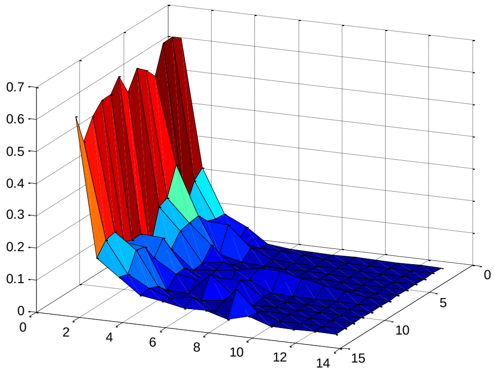
a) 5 min up at 7%



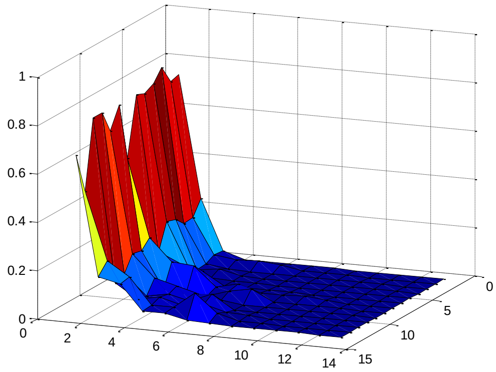
b) 5 min up at 5%



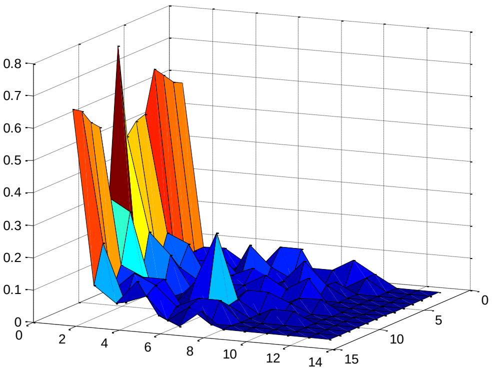
c) 5 min up at 3%



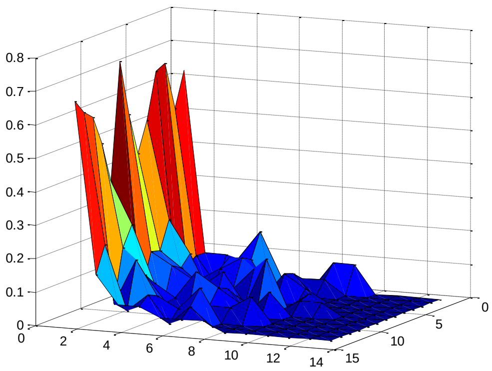
d) 5 min up at 1%



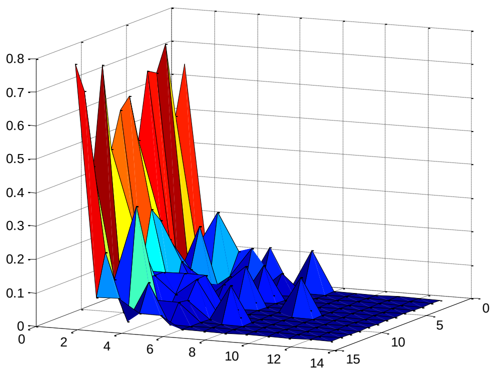
e) 60 min up at 7%



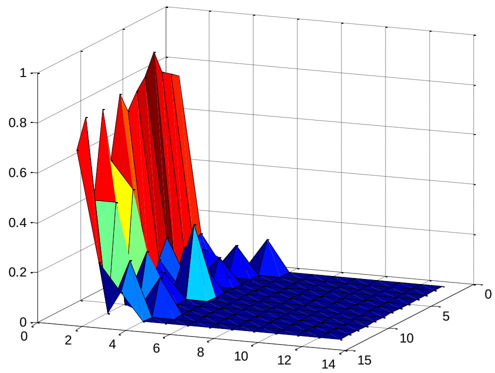
f) 60 min up at 5%



g) 60 min up at 3%



h) 60 min up at 1%

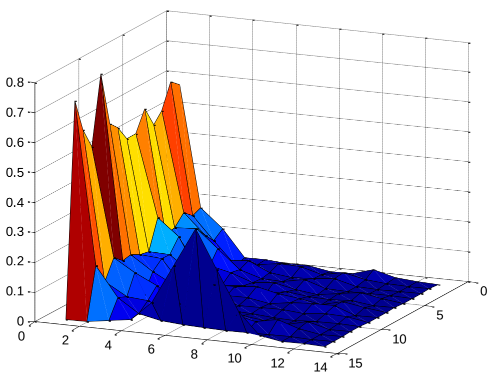


Source: author's calculations

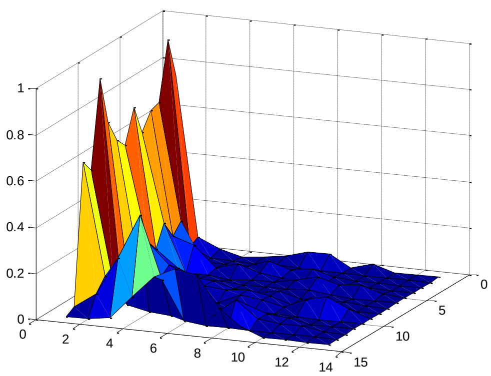
We computed various types of outliers. The ones that were taken into account here show the fact that, if we move further to the tails, we can notice that the isolated outliers (happening in only a few cases) are usually the ones that gain in percentage. This means that, when looking at this kind of correlations, the isolated outliers are the ones that have the highest values. An isolated outlier is similar to a jump in the values of the correlations and therefore we observe an increase in the correlations of some pairs of countries, without a necessary increase in the correlations of the others. An interesting conclusion would be that the countries taken into account here tend to have independent movements in the period we made the analysis.

Figure 2: Simultaneity of outliers for GARCH-DCC correlations

a) DCC 5 min up 5%



b) DCC 5 min up 1%



Source: author's calculations

The computation of the correlations using the GARCH-DCC model showed the same type of structure for the volatilities. We can notice that, when moving from 5% to 1% tail, the upper part of the 5-minute correlations show the same structure as in the case of the rolling correlations. This means that the isolated correlations are larger than the correlations observable for the measurement of the connections of the series a series of returns with all the other series. We can consider this result as a proof that there is no general dependence of correlations at the international level – if we have a large correlation with one country, we do not necessarily have similar correlations with all the other countries. The smaller correlations tend to be present for more than one pair of returns.

Another important aspect is that usually we do not find negative correlations in the upper tails and we do not see too many negative correlations in the lower tails either. The lower tails show negative correlations only in the isolated cases, when we have simultaneity, this is happening for positive but close to zero correlations.

The next point of the analysis consisted in the estimation of the stochastic volatility model according to the specification of Jacquier, Polson and Rossi (1994) for each series of the returns in our sample. The parameters were found using a Markov Chain Monte Carlo technique and a Griddy Gibbs for the Metropolis Hastings algorithm in the estimation of h_t. The parameters estimated after 2500 iterations and burning of 500 iterations helped at the computation of the volatilities for each series of returns. We also used the parameters to compute 1000 Monte Carlo simulations of the returns using these volatilities and we computed the correlations at each step in the Monte Carlo simulation. The results are similar to those already presented, which means that this process provides the same structure of correlations.

We did the same analysis after fitting the Maheu and McCurdy (2007) jump-diffusion model model to each time series and running 1000 Monte Carlo simulations on each pair of correlations. Both the stochastic volatility and a more complex model like this one show the same structure in terms of simultaneity of the returns.

5. Conclusions

Previous research provided interesting analysis of the simultaneity of the outliers for the stock returns computed at the five-minute frequencies. This paper aims at extending these findings to the level of correlations for a sample of 14 stock market index returns for different frequencies ranging from the five-minute returns until the 60-minute returns.

The analysis started with the computation of simple rolling correlations and extended by computing the GARCH-DCC, the stochastic volatility and a complex jump-diffusion model. For the first two models we computed the correlations for each frequency and for different values in the tails (ranging from 7% to 1%). The results showed that the structure of correlations have outliers that are usually isolated among the pairs of correlations available for one national stock market index series of returns. For the stochastic volatility and the jump-diffusion models we used the Monte Carlo simulations to provide possible paths for all the series of returns and computed the coefficients of correlations for each pair. The average results are similar to those already found for the first two ways of computation.

The further analysis will aim at computing the multivariate stochastic volatility model and a dynamic copula model, and perform a similar analysis on the coefficients of dependence.

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