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Effects of the Stock Market Dynamic Linkages on the Central and Eastern European Capital Markets

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***Abstract*—**The interdependences among stock market indices were studied for a long while by academics in the entire world. The current financial crisis opened the door to a wide range of opinions concerning the understanding and measurement of the connections considered to provide the controversial phenomenon of market integration. Using data on the log-returns of 17 stock market indices that include most of the CEE markets, from 2005 until 2009, our paper studies the problem of these dependences using a new methodological tool that takes into account both the volatility clustering effect and the stochastic properties of these linkages through a Dynamic Conditional System of Simultaneous Equations. We find that the crisis is well captured by our model as it provides evidence for the high volatility – high dependence effect.

***Keywords*—**Stock market interdependences, Dynamic System of Simultaneous Equations, financial crisis

I. Introduction

THE current financial crisis opened the door to a wide range of opinions concerning the understanding and measurement of the connections considered to provide the controversial phenomenon of market integration. As it is explained in [1], in finance, markets are considered integrated when assets of the same risk offer the same expected return irrespective of their domicile. Financial liberalization, characterized especially by privatization, bank reform and unrestricted capital flows should theoretically determine the market integration of emerging and developing markets (such as CEE markets) with the global capital market. This happens because, as a result of financial liberalization, foreign investors bid up the prices of equities previously unavailable to them, which now provide diversification benefits. As a result, the cost of equity should decrease, which in turn increases investment and economic welfare in the newly liberalized country.

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The objective of this paper is to investigate, model and explain the dynamic interdependence of Central and Eastern European stock markets as well as the linkages between developed markets such as the US, UK and Japan on one hand and developing stock markets in the CEE region on the other. Previous findings attest that dramatic movements in one stock market can have a significant impact on other markets of different sizes or structures across the world. This is why we are particularly interested in whether the linkages between these markets have changed as a result of the recent global financial crisis and, if so, to what extend and in what direction have the connections between markets changed as a result of the crisis. We investigate 17 stock markets indices, including both developing CEE markets and developed stock markets and try to discover interdependencies both in term of price and volatility transmission through a Dynamic Conditional System of Simultaneous Equations.

The study is organized as follows. Section 1 undertakes an extensive literature review in the field of stock market interdependence. Section 2 presents the data and defines the methodology to be used in the empirical investigation. In section 3, we present and analyze the estimation results. Finally, section 4 summarizes the main findings of the paper, draws conclusions and suggests future related research.

II. Literature review

Many empirical studies in the financial literature report substantial evidence of interdependency among world financial markets both in the short and the long run.

[10] found a substantial amount of multi-lateral interaction among the nine largest stock markets in the world (Australia, Canada, France, Germany, Hong Kong, Japan, Switzerland, the United Kingdom and the United States). In particular, they documented that shocks in the US market have the most important impact on the other national markets included in the study. [15] investigate the price and volatility spillovers in three major stock markets (New York, Tokyo, and London) and documented evidence for spillover effects from New York to Tokyo and London and from London to Tokyo, but not from Tokyo to either to New York or London. [20] found significant spillovers among the Pacific Rim countries, and [3]) show that the Scandinavian stock markets exhibit interdependencies both in term of price and volatility transmission. [19] study both Asian markets and developed

countries of the OECD and find evidence of interdependency among the two categories of markets. They also attest that the markets of the USA and Britain have a dominant role both in the short and the long-run.

[16] examines dynamic interdependence, volatility transmission, and market integration across Asian stock markets during the Asian financial crisis periods 1997 and 1998. They employ a vector autoregressive–exponential generalized autoregressive conditional heteroskedasticity (VAR-EGARCH) model and report that reciprocal volatility transmission existed between Hong Kong and Korea, and unidirectional volatility transmission from Korea to Thailand.

[11] examines financial market comovements across European transition economies and observes that the pattern of high-frequency spillovers during the Russian crisis looks very similar to that observed in other regions during turbulent times. [23] investigate whether is it bank lending or trade linkages and country characteristics that help explain contagion and find evidence in favor of a common lender effect in the Mexican, Thai, and Russian crises, after controlling for the degree of trade competition and macroeconomic fundamentals. [9] empirically estimates cross-section and time-series models to determine the fundamental factors that influence the correlation and evolvement of the correlation between emerging stock markets. [4] investigate stock market linkages in Latin America and report that there is cointegration among the analyzed markets (Brazil, Mexico, Chile, Argentina, Kolombia, and Venezuela) up to 1999, but the relationship is no longer significant thereafter. [2] investigate the dynamic structure of nine major stock markets using an error correction model and directed acyclic graphs (DAG) and report that the US market is highly influenced by its own historical innovations, but it is also influenced by market innovations from the UK, Switzerland, Hong Kong, France and Germany. They also show that US market is the only market that has a consistently strong impact on price movements in other major stock markets in the longer-run. [12] examine, through Cointegration tests, the short and long-run relationships between major world financial markets with particular attention to the Greek stock exchange and confirm the dominance of the USA financial market and the strong influence of DAX and FTSE on all other markets of the sample. [18] analyze the possibility to provide a forecast for the sign of the financial asset returns using the empirical prices of stocks listed at the Bucharest Stock Exchange. They confirm previous research about the fact that a wide class of statistics (the direction of change in this case) are time dependent in a GARCH manner. [5] employ the dynamic conditional correlation and the spillover index in order to assess the interdependence between equity markets in the EMEAP region and the US, and across the EMEAP markets and show that equity market interdependence has increased steadily since early 2006, and rose sharply following the collapse of the Lehman Brothers in September 2008. [21] and other developed markets during a period in which the manifestations of the recent global financial crisis were most visible on the Romanian stock market (2007-2009). The study confirms that the US stock market was the most influential during the analyzed period and innovations in the United States stock market were subsequently transmitted to the other analyzed markets, including the Romanian market. In addition, this relationship was unilateral, as stock movements from other markets were not necessarily reflected in future US stock prices. Further, [22] studies the Romanian stock market over the period 2002 – 2008 and the results suggest that although firm-specific financial indicators are important risk factors and help explain time-variation in Romanian common stocks returns, global risks are also conditionally priced. Finally [17] use data on the stock market indices from 2005 until 2009 to check for time changes in the dynamics of the correlation coefficients. The correlations are modeled in a GARCH-like manner and provide the basics for the methodological developments of our paper. They also evidenced the contagion effect according to which the markets showed increased correlations around the crisis.

In conclusion, the majority of empirical findings attest that over the last decades international stock markets have become increasingly interdependent. In addition, the role of the USA market worldwide is dominant and the evolution of US stock indices has an important impact on the majority of financial markets.

III. DATA AND METHODOLOGY

We use data on the evolution of the stock market indices from MSCI (Morgan Stanley Capital Indices - Barra), with daily frequencies, from November 30th 2005 until April 1st 2009, providing a sample size of 870 for the daily log-returns. We took into account the following 17 national stock markets: Czech Republic, Hungary, Bulgaria, Croatia, the Eastern European MSCI composite index, Poland, Russia, Turkey, Romania, Slovenia, the MSCI European composite stock index, Austria, France, Germany, Japan, United Kingdom and USA.

The table shows that none of the log-returns have a normal distribution as showed by the Jarque-Bera test, which is a fact evidenced by previous research. We also notice the evidence of other so-called stylized facts, such as the fact that the distribution is usually negatively skewed (less Germany and France) and has fat tails for the whole period of our analysis.

Previous research (Cont 2001 among others) showed that one of the most important properties of the stock market returns (indices included) is the heteroskedasticity especially at high frequency log-returns, such as the daily frequency we are using. Besides this, the history dependence of the squared returns, seen as a proxy for the daily variance, favored the development of the GARCH family of models.

TABLE I DESCRIPTIVE STATISTICS OF THE STOCK INDEX LOG-RETURNS NOVEMBER 30TH 2005 TO APRIL 1ST 2009

	CZREP	HUN	BUL	CRO	CEE	POL	RUSS	TUR
Mean	-0.000174	-0.001191	-0.001759	-0.000136	-0.000833	-0.000842	-0.000808	-0.000879
Std. Dev.	0.021264	0.025898	0.020271	0.016239	0.025349	0.022244	0.030283	0.029123
Skewness	-0.334556	-0.237944	-1.943.532	-0.09406	-0.32243	-0.378179	-0.299505	-0.224963
Kurtosis	1.624.924	1.262.629	1.802.116	1.029.922	1.483.967	640.211	1.769.671	5.874.079
Jarque-Bera	6.379.638	3.367.335	8726.99	1.932.632	5.096.522	4.403.081	7.842.763	3.067.751
Probability	0	0	0	0	0	0	0	0
	RO	SLOV	AU	FR	GER	JAP	UK	USA
Mean	-0.001405	-7.66E-05	-0.001177	-0.000535	-0.000413	-0.000653	-0.000722	-0.000622
Std. Dev.	0.024871	0.015685	0.021788	0.016598	0.016092	0.016929	0.017042	0.017585
Skewness	-293.663	-0.351792	-0.102134	0.094948	0.244905	-0.038126	-0.093268	-0.050266
Kurtosis	4.105.366	1.047.227	9.464.534	1.070.096	1.183.499	7.357.958	1.007.763	9.596.393
Jarque-Bera	53743.38	2.041.959	1.516.407	2.151.104	2.838.263	6.886.634	1.817.129	1.577.691
Probability	0	0	0	0	0	0	0	0

Therefore, our model takes into account the clustering of volatilities for the daily log-returns of the stock market indices and captures the interdependences of these returns on a daily basis, after controlling for this phenomenon. This will bring us more tractability in the application of our method of time dependent system of equations, as the residuals are presumed to show no heteroskedasticity.

Thus, our first manipulation of the data dealt with the computation of simple GARCH(1,1) coefficients for the log-returns for each of the 17 international indices. All the computations were performed in Matlab and the Q-Q plots (not produced here due to lack of space) on the standardized returns, obtained after the calibration of the models, showed that the conditionality of the squared returns disappeared. We consider that the models succeeded to capture a great deal of the variation of these returns.

In the next step we based our analysis on the principle of the Dynamic Conditional Correlation model that considers the correlations to be stochastic and to change in a GARCH like manner. Thus, the DCC model is based on the modeling of the daily covariances (that are allowed to change in the same way the volatilities are allowed to change in GARCH family of models) as exponentially smoothed average of the products of the historical realizations of each of the two variables, starting from $\sigma_{ij,t+1} = \frac{1}{m}\sum_{\tau=1}^{m} R_{i,t+1-\tau} R_{j,t+1-\tau}$, where there is no clear specification for the choice of *m*, and going to the GARCH (1,1) specification

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

which allows for a long run average covariance , equal to $\sigma_{ij} = \omega_{ij} / (1-\alpha-\beta)$, and also permits the identification of an optimal number of observations *m*.

The passing to correlation takes into account the simple formula $\rho_{ij,t+1} = \sigma_{ij,t+1} / (\sigma_{i,t+1}\sigma_{j,t+1})$, which means that, besides covariances, we also need estimates for the variances, or the standard deviations of the log-returns. The DCC model assumes that all of these elements are stochastic and are strongly dependent on their previous realizations in a manner that allows them to revert to their long term averages. Hence, one model for their dynamics is

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

The DCC allows for the estimation of the coefficients for the three GARCH models (one for the covariance and two for each of the variances) using the quasi maximum likelihood estimation method.

To insure the tractability of the method we use the same coefficients for all of the three models. We consider this not to be a too strong assumption as we are not using raw returns but the standardized ones, in which the volatility conditionality was taken out by using specific models for each of the series of log-returns. On the other hand, this will help us to establish the property of positive definiteness for the variance-covariance matrices.

The methodology we are proposing here deals with the construction of a system of simultaneous equations in which each of the series of log-returns belonging to the indices will be considered to be dependent on all of the other 16 series of log-returns. We propose a model in which we estimate the coefficients for all the 17 equations at each point in time, by looking at their dependence on their own previous realizations.

$$\begin{cases} R_1 = \beta_{1,2} R_2 + \beta_{1,3} R_3 + \dots + \beta_{1,17} R_{17} \\ R_2 = \beta_{2,1} R_1 + \beta_{2,3} R_3 + \dots + \beta_{2,17} R_{17} \\ \vdots \\ R_{17} = \beta_{17,1} R_1 + \beta_{17,2} R_2 + \dots + \beta_{17,16} R_{16} \end{cases}$$

As in the case of the DCC model, our model assumes that the residuals (standardized returns) follow a bivariate normal distribution for each pair of index returns taken into account. We compute the beta coefficients for the multiple regressions in each equation of the Simultaneous Equation Model by minimizing the bivariate normal log-likelihood function. The function is

$$L_c = -\frac{1}{2}\sum_{t=1}^{T}(\ln(1-\rho_{12,t}^2) + \frac{z_{1,t}^2 + z_{2,t}^2 - 2\rho_{12,t} z_{1,t} z_{2,t}}{(1-\rho_{12,t}^2)})$$

where z_1 and z_2 represent the standardized returns.

We will consider each equation in our system to be estimated separately. To show the estimation procedure, we write the equation in the following manner:

$$\underset{(n\times 1)}{Y} = \underset{(n\times k)}{X}\ \underset{(k\times 1)}{\beta}$$

Multiplying on the left side by X^T, we obtain the following equation that will help us to provide estimations for the Dynamic System on an equation by equation manner.

$$\underset{(k\times 1)}{X^T Y} = \underset{(k\times k)}{X^T X}\ \underset{(k\times 1)}{\beta},$$

which can also be written as

$$\begin{pmatrix} \sum y x_1 \\ \vdots \\ \sum y x_k \end{pmatrix} = \begin{pmatrix} \sum x_1^2 & \cdots & \sum x_k x_1 \\ \vdots & \ddots & \vdots \\ \sum x_k x_1 & \cdots & \sum x_k^2 \end{pmatrix} \begin{pmatrix} \beta_1 \\ \vdots \\ \beta_k \end{pmatrix}$$

We use the Dynamic Conditional Correlation methodology to obtain values at each moment in time for the elements of the matrix $(X^TX)^{-1}$ for each equation in our system. We use here the fact that the product of each pair of log-returns tends at the limit of many observations to the value of the covariance between the two variables, while the squared values of the log-returns converge to the variance of the random variable. Hence, the value of the product $x_i x_j$ at moment t is a proxy for the value of the covariance between the two random variables at t, and the value x_i^2 is a proxy for the realization of the variance at the same moment t. The dynamic correlations are computed by the MLE criteria for each pair of returns and then we build the covariance by multiplying the DCC with the product of standardized returns for each moment in time t. Therefore, for each moment t we estimate the following matrix of coefficients

$$\begin{pmatrix} & \beta_{2,t} & \beta_{3,t} & \cdots & \beta_{16,t} & \beta_{17,t} \\ \beta_{1,t} & & \beta_{3,t} & \cdots & \beta_{16,t} & \beta_{17,t} \\ \beta_{1,t} & \beta_{2,t} & & \cdots & \beta_{16,t} & \beta_{17,t} \\ \vdots & \vdots & \vdots & \vdots & & \vdots \\ \beta_{1,t} & \beta_{2,t} & \beta_{3,t} & \cdots & \beta_{16,t} & \end{pmatrix}$$

Each row in the previous matrix is the result of the calculation of of the $(X^TX)^{-1}X^TY$ matrix and each element of these matrices is produced by taking into account the conditional property of each coefficient. We will therefore end up with 272 coefficients for each of the 870 moments in our sample of returns.

The next step in our empirical analysis deals with the computation of the significance of each of these beta coefficients. The significance will be obtained by computing the t-statistics and then the p-values for the t-statistics that have a student t distribution.

Our assumption here is that the squared residuals for each moment t represent the proxy for the estimation of the variance of the residuals at the respective moment t. The significance for each of the beta coefficients will be computed by dividing the value of the coefficient at moment t to its standard deviation at the same moment in time. The variance covariance matrix for all the beta coefficients in a regression is given by $\sigma^2(X^TX)^{-1}$, where σ^2 is the variance of the residuals. Therefore, the estimation of the standard deviation for the beta coefficients can be realized using the same (X^TX) matrix, whose elements we have already estimated.

IV. Empirical Results

The maximization of the bivariate normal loglikelihood function had as result the estimation of the GARCH coefficients for the mixed products and the squared values of the realizations of the log-returns – the three equations. Our Matlab program provided 870 matrices of 17 x 16 coefficients for each day from November 30th 2005 until 1st of April 2009 and another 870 matrices with the p-values computed on the t-statistics for each parameter in each day. As previously stated, our purpose is to study the interdependences among these 17 indices by looking at the period before the crisis and the period after that. For lack of space we only produced here a table showing the number of significant coefficients for each of these two periods, considering that the moment of the financial crisis was 15th of September 2008, when Lehman Brothers filed for Chapter 11. Therefore, each of the cells of Table 2 show the percentage of significant coefficients, both before and after the crisis, for the regressions where the dependent variables are the indices specified on the first column of the table and the explanatory variables are the indices on the first row of the table. We notice that the structure of the significance in broadly kept after the crisis. Figure 1 shows the spreading of these percentages in a manner that helps us to understand that the number of significant coefficients is reduced when we compare the situation after the crisis with what happened before the crisis. This means that the interdependences among the 17 indices are reduced after the crisis, probably making room for other factors to determine the dynamics of the daily log-returns.

TABLE II STATISTICAL SIGNIFICANCE OF THE BETA COEFFICIENTS IN THE SIMULTANEOUS EQUATIONS MODEL. PRIOR MEANS PERCENTAGE OF P-VALUES THAT WERE LOWER THAN 5% BEFORE 15TH OF SEPTEMBER 2008 AND POSTERIOR MEANS PERCENTAGE OF SIGNIFICANCE AFTER THIS DATE

	Years	**CZ**	**HU**	**BU**	**CR**	**CE**	**PO**	**RU**	**TU**	**RO**	**SL**	**EU**	**AU**	**FR**	**GER**	**JAP**	**UK**	**USA**
CZ	Prior		46%	45%	44%	47%	50%	47%	47%	46%	41%	45%	49%	44%	43%	45%	44%	45%
	Post		49%	34%	49%	44%	53%	37%	38%	49%	44%	46%	42%	48%	44%	41%	42%	34%
HU	Prior	47%		45%	46%	51%	59%	43%	48%	45%	41%	47%	45%	46%	44%	45%	45%	42%
	Post	46%		34%	40%	41%	49%	36%	43%	44%	46%	40%	45%	40%	39%	40%	35%	39%
BUL	Prior	46%	45%		43%	41%	42%	41%	41%	42%	42%	43%	43%	42%	41%	42%	39%	41%
	Post	39%	43%		46%	45%	48%	37%	42%	37%	42%	42%	39%	40%	40%	37%	39%	35%
CRo	Prior	43%	46%	43%		42%	46%	42%	45%	46%	42%	43%	44%	42%	41%	43%	42%	44%
	Post	51%	48%	45%		41%	45%	42%	40%	46%	55%	46%	50%	39%	36%	51%	35%	44%
CEE	Prior	46%	50%	44%	41%		52%	81%	47%	44%	42%	46%	43%	46%	42%	45%	46%	46%
	Post	46%	48%	34%	42%		39%	76%	39%	44%	39%	37%	46%	35%	39%	47%	35%	39%
POL	Prior	50%	58%	43%	46%	52%		41%	50%	46%	42%	46%	43%	44%	42%	48%	42%	43%
	Post	53%	52%	39%	46%	40%		35%	50%	48%	45%	44%	41%	37%	35%	39%	42%	39%
RUS	Prior	48%	44%	44%	42%	82%	41%		49%	44%	41%	46%	44%	45%	46%	44%	46%	46%
	Post	39%	37%	27%	39%	77%	35%		36%	41%	42%	33%	46%	34%	39%	42%	32%	43%
TUR	Prior	47%	48%	39%	43%	47%	49%	46%		49%	37%	47%	45%	46%	46%	47%	43%	48%
	Post	42%	47%	38%	43%	42%	49%	43%		40%	46%	47%	43%	42%	53%	46%	44%	49%
RO	Prior	45%	43%	40%	45%	42%	45%	42%	47%		43%	41%	48%	45%	39%	48%	42%	40%
	Post	46%	44%	37%	46%	39%	48%	39%	38%		46%	40%	45%	42%	54%	37%	37%	37%
SLO	Prior	40%	41%	40%	44%	41%	41%	41%	39%	44%		42%	40%	37%	41%	43%	39%	43%
	Post	37%	45%	30%	50%	38%	37%	44%	37%	44%		37%	37%	37%	32%	52%	35%	37%
EU	Prior	45%	47%	44%	43%	45%	46%	46%	50%	43%	43%		49%	58%	63%	45%	66%	49%
	Post	51%	52%	42%	50%	37%	47%	35%	46%	46%	46%		55%	58%	63%	42%	62%	43%
AU	Prior	48%	44%	41%	45%	43%	43%	43%	46%	48%	40%	49%		45%	46%	44%	46%	44%
	Post	39%	46%	31%	49%	45%	41%	47%	38%	42%	36%	49%		44%	48%	40%	37%	36%
FR	Prior	43%	45%	42%	44%	47%	44%	46%	48%	46%	39%	57%	45%		58%	46%	47%	50%
	Post	47%	46%	43%	39%	38%	40%	37%	39%	47%	42%	55%	46%		56%	41%	54%	51%
GER	Prior	44%	43%	43%	42%	42%	44%	45%	48%	41%	43%	64%	47%	59%		45%	53%	48%
	Post	46%	45%	39%	39%	38%	40%	43%	51%	54%	39%	59%	49%	54%		48%	49%	49%
JAP	Prior	43%	43%	40%	45%	45%	48%	43%	48%	47%	42%	44%	44%	45%	42%		40%	47%
	Post	33%	41%	32%	49%	37%	35%	30%	30%	32%	56%	35%	38%	37%	37%		34%	42%
UK	Prior	45%	46%	44%	43%	47%	45%	48%	46%	45%	39%	67%	48%	49%	54%	44%		54%
	Post	48%	43%	41%	41%	36%	45%	37%	42%	45%	39%	61%	41%	56%	51%	44%		51%
USA	Prior	42%	42%	39%	43%	44%	42%	46%	46%	40%	42%	48%	43%	50%	47%	46%	52%	
	Post	30%	41%	26%	39%	34%	34%	38%	43%	37%	32%	34%	37%	49%	46%	44%	44%	

We also notice that the bulk of the coefficients are significant in about 40% - 50% of the cases, which means that they are not consistent. However, there are 32 coefficients that showed significance in more than 50% of the cases for the sample before the crisis and 33 coefficients showing significance in more than 50% of the cases in the post-crisis period.

V. CONCLUSION

Our purpose in this paper was to use a new model in order to explain the dynamic interdependence of Central and Eastern European stock markets as well as the linkages between developed markets such as the US, UK and Japan on one hand and developing stock markets in the CEE region on the other. We start from results provided by previous findings, which attest that dramatic movements in one stock market can have a significant impact on other markets of different sizes or structures across the world.

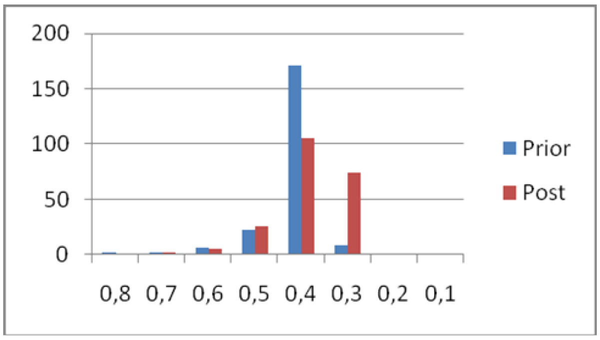

Fig. 1 Percentage of significant coefficients

This is why we focused on the dynamics of the linkages between these markets to inquire the way they have changed as a result of the recent global financial crisis. We used 17 stock markets indices, including both developing CEE markets and developed stock markets and try to discover interdependencies both in term of price and volatility transmission through a new methodology (to our knowledge) that creates a Dynamic Conditional System of Simultaneous Equations. After controlling for the conditional volatility of each series of log-returns for the 17 stock market indices, using a simple GARCH(1,1) model, we built a system of simultaneous equations for the resulting standardized returns. The matrix of 17 x 16 regression coefficients was allowed to change in time for all the 870 days of our sample. We analyzed the significance of these parameters for the period before the crisis and the period after and we found that the percentage of significant coefficients reduced after the crisis, which means that after the crisis there might be other factors determining their movements, besides the other capital markets themselves.

As this is the first time we are using this methodology for such an analysis, we plan to investigate more methodological as well as economic issues.

On one hand we plan to extend the methodology to transform it to a Vector Auto-Regression by including lags of the explanatory variables too. The choice of the lags could be realized using criteria like Akaike and Schwartz, computed for the bivariate normal log-likelihood function for each pair of variables. The VAR can also be extended by using other factors than simply the external indices.

On the other hand the vector of coefficients for the same relationship between a pair of returns can be tested by a regime shifting scheme to pick up potential changes in the factors affecting the dynamics of the stock markets. These models can also be used to perform event-study analysis to check for the reaction of the global system of stock markets to different economic events that have the potential to produce systemic events.

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