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CONTAGION ACROSS CENTRAL AND EASTERN EUROPEAN STOCK MARKETS: A DYNAMIC CONDITIONAL CORRELATION TEST

Abstract. *Economic literature suggests that contagion can occur because of trade links, both direct trade among countries and competition in third markets; similar initial conditions, whereby countries co-move insofar as they have similar macroeconomic (or other) characteristics; and financial linkages. While contagion can take many forms, this paper tests for stock market contagion during recent financial crises among CEE economies, comparing with some Western European countries, USA and Japan markets and test for the existence of contagion. It defines contagion as a significant increase in market co-movement after a shock to one country (or group of countries). We found that the correlations become more statistically significant as we go from the early stages of our sample towards the end of it. Our test takes into account the fact that the correlations can change from one day to another and it can provide powerful evidence in the support of the phenomenon of contagion.*
Key words: *contagion, dynamic conditional correlations, GARCH models*

JEL classification: C22, G15, P59

1. Introduction

A number of currency and financial crises affected international financial markets in the last decade, with considerable negative effect on emerging market countries. Generally, these crises have been characterized by contagious effects, a crisis occurring in one country spreads to other countries, either in the neighborhood or around the globe.

The new contagious feature has triggered a large research effort, both at the theoretical and empirical levels. In the economic literature, contagion is seen as a significant change in the way that shocks are propagated across countries. One might conclude that contagion exists while it is really the presence of external shocks that leads a group of countries to suffer from contemporaneous speculative attacks and financial crises.

Even if the financial system of the Central and East European (CEE) countries is mainly bank dominated, the stock exchanges registered a considerable progress and appear to be well integrated with world financial markets. Being that these markets are small compared to the stock exchanges of the developed countries, they are sensitive to shifts in regional and world-wide portfolio adjustments of large investments fund and other market participants. This is why these markets are considered to be more volatile than well-established stock markets.

There is widespread disagreement about what *contagion* entails. Some define contagion as a significant increase in cross-market linkages after a shock to one country (or group of countries). Cross-market linkages can be measured by a number of different statistics, such as the correlation in asset returns, the probability of a speculative attack, or the transmission of shocks or volatility. According to this definition, if two markets show a moderate degree of co-movement during periods of stability, and then a shock to one market leads to a significant increase in market co-movement, this would constitute contagion. On the other hand, if two markets show a high degree of co-movement during periods of stability, even if they continue to be highly correlated after a shock to one market, this may not constitute contagion. It is only contagion if cross-market co-movement increases significantly after the shock. If the co-movement does not increase significantly, then any continued high level of market co-movement suggests strong linkages between the two economies which exist in all states of the world. This is what we is called interdependence. Based on this approach, contagion implies that cross-market linkages are fundamentally different after a shock to one market, while interdependence implies no significant change in cross-market relationships during a crisis.

Forbes and Rigobon (1999) propose using the term "shift-contagion" instead of "contagion" in order to clarify exactly what this term entails. The term shift-contagion is sensible because it not only clarifies that contagion arises from a shift in cross-market linkages, but it also avoids taking a stance on how this shift occurred.

Some economists argue that contagion occurs whenever a shock to one country is transmitted to another country, even if there is no significant change in cross-market relationships. Others argue that it is impossible to define contagion using tests for changes in cross-market linkages. Instead, they argue that it is necessary to identify exactly how a shock is propagated across countries, and only certain types of transmission mechanisms (no matter what the magnitude) constitute contagion.

Economic literature suggests that contagion can occur because of trade links, both direct trade among countries and competition in third markets; similar initial conditions, whereby countries co-move insofar as they have similar macroeconomic (or other) characteristics; and financial linkages.

While contagion can take many forms, this paper tests for stock market contagion during recent financial crises among CEE economies, comparing with some Western European countries, USA and Japan markets and test for the existence of contagion. It defines contagion as a significant increase in market co-movement after a shock to one country (or group of countries).

This definition provides a straightforward framework for testing if contagion occurs, simply comparing the correlation (or covariance) between two markets during a relatively stable period (generally measured as a historic average) with that during a period of turmoil (directly after a shock occurs). Contagion is a significant increase in the cross-market relationship during the period of turmoil. A second benefit of this definition of contagion is that it provides a straightforward method of distinguishing between alternative explanations of how shocks are transmitted across markets. There is an extensive theoretical literature on the international propagation of shocks. Many theories assume that investors (or institutions) behave differently after a large negative shock. Other theories argue that most shocks are propagated through real linkages, such as trade. It is extremely difficult to measure these various transmission mechanisms directly. By defining contagion as a significant increase in cross-market linkages, this paper avoids to directly measure and differentiate between these various propagation mechanisms. Moreover, tests based on this definition provide a useful method of classifying theories as those which entail either a change in propagation mechanisms after a shock versus those which are a continuation of existing mechanisms. Identifying if this type of contagion exists could therefore provide evidence for or against certain theories of transmission.

2. Literature review

The existing literature promotes a number of alternative methods to test for the presence of contagion during financial market crises. A range of different methodologies are in use, making it difficult to assess the evidence for and against contagion, and particularly its significance in transmitting crises between countries.

The origins of current empirical studies of contagion stems from Sharpe (1964) and Grubel and Fadner (1971), and more recently from King and Wadhini (1990), Engle, Ito and Lin (1990) and Bekaert and Hodrick (1992). Many of the methods proposed in these papers are adapted in some form to the current empirical literature on measuring contagion.

Recently, research has been intensified to study the issue CEE countries, especially after European Union enlargement.

Scheicher (2001) studies the regional and global integration of stock markets in Hungary, Poland and the Czech Republic and finds evidence of limited interaction: in returns, both regional and global shocks are identified, but innovations to volatility exhibit a chiefly regional character. The markets exhibit low correlations with international markets as well. Tse, Wu, and Young (2003) investigate the international information transmission between the US and Polish stock markets using daily return data. They show that there is no volatility spillover between these two markets and that these two markets are not driven by a long-run common trend. However, there is a mean spillover running from the New York Stock Exchange to the Warsaw Stock Exchange (WSE) in the EGARCH model (weak evidence of the short-run influence of the US market on the performance of the WSE). By contrast, the WSE has virtually no influence on the US market.

Syriopoulos (2004) found that the individual Central European markets tend to display stronger linkages with their mature counterparts than with neighboring markets.

Looking for possible interrelations within three stock markets in Central and Eastern Europe and interconnections which may exists between Western European stock markets on the one hand (DAX, CAC, UKX) and Central and Eastern European stock markets (BUX, PX-50, WIG20) on the other Egert and Kocenda (2005) argue that, for a common daily window composed of 72 ticks running from mid-2003 to the early 2005, no robust cointegration relationship could be established for any of the stock index pairs or for any of the extended specifications. Notwithstanding the lack of any stable long-term relation between the stock market indices under study, there are signs of short-term spillover effects both in terms of stock returns and stock price volatility. Granger causality tests show the presence of bidirectional causality for the returns as well as volatility series. In general, it appears that spillover effects are stronger from volatility to volatility as compared to contagion effects from return to return series.

Patev, Kanaryan and Lyroudi (2006) investigated the CEE equity market co-movements before, during and after major emerging market crises and examined the impact of the crisis on the gains of international portfolio diversification in CEE. They found no long-run relationship between the US and the four Central European stock markets and a feedback effect and causality in one direction during and after the crisis period. The authors confirm a decrease of portfolio benefits in the crisis period and an increase of portfolio benefits in the post-crisis period.

3. Data and Methodology

3.1 Methodology

GARCH models are designed to capture certain characteristics that are commonly associated with financial time series: Fat tails Volatility clustering Leverage effects Probability distributions for asset returns often exhibit fatter tails than the standard normal, or Gaussian, distribution. The fat tail phenomenon is known as excess kurtosis. Time series that exhibit a fat tail distribution are often referred to as leptokurtic.

In addition, financial time series usually exhibit a characteristic known as volatility clustering, in which large changes tend to follow large changes, and small changes tend to follow small changes. In either case, the changes from one period to the next are typically of unpredictable sign. Large disturbances, positive or negative, become part of the information set used to construct the variance forecast of the next period's disturbance. In this manner, large shocks of either sign are allowed to persist, and can influence the volatility forecasts for several periods. Volatility clustering, or persistence, suggests a time-series model in which successive disturbances, although uncorrelated, are nonetheless serially dependent.

Volatility clustering (a type of heteroscedasticity) accounts for some but not all of the fat tail effect (or excess kurtosis) typically observed in financial data. A part of the fat tail effect can also result from the presence of non-Gaussian asset return distributions that just happen to have fat tails, such as Student's t. Finally, certain classes of asymmetric GARCH models are also capable of capturing the so-called leverage effect, in which asset returns are often observed to be negatively correlated with changes is volatility. That is, for certain asset classes, most notably equities but excluding foreign exchange, volatility tend to rise in response to lower than expected returns and to fall in response to higher than expected returns. Such an effect suggests GARCH models that include an asymmetric response to positive and negative surprises.

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

$$\omega' \sum\nolimits_{t+1} \omega \geq 0$$

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.

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 modeled 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 $E_t(z_{i,t+1}^2) = E_t(z_{2,t+1}^2) = 1$ 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

$$Q_{t+1} = E\left[z_t z_t^{;}\right](1 - \alpha - \beta) + \beta Q_t.$$

In the two asset case we have

$$\begin{bmatrix} q_{11,t+1} & q_{12,t+1} \\ q_{12,t+1} & q_{22,t+1} \end{bmatrix} = \begin{bmatrix} 1 & \rho_{12} \\ \rho_{12} & 1 \end{bmatrix}(1 - \alpha - \beta)\begin{bmatrix} z_{1,t}^2 & z_{1,t}z_{2,t} \\ z_{1,t}z_{2,t} & z_{2,t}^2 \end{bmatrix} + \beta\begin{bmatrix} q_{11,t} & q_{12,t} \\ q_{12,t} & q_{22,t} \end{bmatrix}$$

where ρ_{12} is the unconditional correlation between the two assets, which can be estimated in advance as

$$\rho_{12} = \frac{1}{T}\sum_{t=1}^{T} z_{1,t}z_{2,t}.$$

An important feature of these models is that the matrix Q_{t+1} is positive definite as it is a weighted average of positive semi-definite and positive definite matrices. This will in turn ensure that the correlation matrix Γ_{t+1} and the covariance matrix, Σ_{t+1}, will be positive semidefinite as required.

Another important practical advantage of this model is that we can estimate the parameters in a sequential fashion. First all the individual variances are estimated one by one. Second, the returns are standardized and the unconditional correlation matrix is estimated. Third, the correlation persistence parameters α and β are estimated. The key issue is that only very few parameters are estimated simultaneously using numerical optimization. This feature makes the dynamic correlation models considered here extremely tractable.

Quasi Maximum Likelihood Estimation

In estimating the dynamic conditional correlation models suggested above, we can rely on the quasi maximum likelihood estimation (QMLE) method. In the case of two assets, we can use the bivariate normal distribution function for $z_{1,t}$ and $z_{2,t}$ to write the likelihood as

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

where $\rho_{12,t}$ is given from the particular correlation model being estimated, and the normalization rule. Hence

$$\rho_{12,t} = \frac{q_{12,t-1}}{\sqrt{q_{11,t-1}q_{22,t-1}}}$$

where:

$$q_{11,t} = \omega + \alpha z_{1,t-1}z_{1,t-1} + \beta q_{11,t-1}$$
$$q_{12,t} = \omega + \alpha z_{1,t-1}z_{2,t-1} + \beta q_{12,t-1}$$
$$q_{22,t} = \omega + \alpha z_{2,t-1}z_{2,t-1} + \beta q_{22,t-1}$$

We find the optimal correlation parameters by maximizing the correlation loglikelihood function, L_c. In order to initialize the dynamics, we set $q_{11,0} = 1$, $q_{22,0} = 1$, and $q_{12,0} = \frac{1}{T}\sum_{t=1}^{T} z_{1,t}z_{2,t}$. The variables which enter the likelihood are the rescaled returns, z_t and not the original raw returns, R_t themselves. We are essentially treating the standardized returns as actual observations here.

3.2 Data

The data consists in stock market indices from MSCI, with a daily frequency and starting from November 30th 2005 until April 1st 2009, which resulted in 870 daily log-returns. The indices that we used cover the following 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, totaling 17 national stock indices.

4. Results

The GARCH and the DCC models were calibrated on the 870 daily returns and all the coefficients were computed for the 17 markets that were taken into account. As presented in the methodology part of the paper, we calibrated a GARCH model for each of the 17 series and we computed the daily standard deviations for the whole period. These standard deviations were used in order to compute the standardized returns, by dividing the absolute values of the log-returns to the standard deviations computed in each day. These standardized values of the returns were used to calibrate the DCC model for each pair of two national stock indices in our sample. Hence, we obtained a three dimensional matrix of the size 870 x 17 x 17, which consists in all the daily correlations for each pair of two indices in our sample. We have, in this way a multivariate representation of the linear relations that characterize the dynamics of all the indices in the respective period.

For lack of space we tried to present here some of the results that summarize our findings. In order to provide such a report, we computed the means of all the correlations for each pair of two indices in our sample, together with all the p-values computed for a t-statistic that tests for the statistical significance of the means we have at hand, for each year in our sample. As we did not include many days from 2005 we reported the means and the p-values for both 2005 and 2006 taken together. These results are presented in table 1.

We can see that the general movement of all the correlations in the period we look at is towards an increase in the values of the means for the conditional correlations and a reduction of the p-values, which is evidence for an increase in the statistical significance of these correlations.

Table 1 – The averages of all the means of the daily correlations for the years in the sample

	CZECH REPUBLIC		HUNGARY		BULGARIA		CROATIA	
	Means	p-values	Means	p-values	Means	p-values	Means	p-values
2005 and 2006	0,34	0,09	0,33	0,12	0,02	0,32	0,12	0,26
2007	0,35	0,11	0,38	0,11	0,03	0,38	0,20	0,19
2008	0,39	0,07	0,45	0,05	0,17	0,16	0,32	0,10
2009	0,43	0,07	0,34	0,10	0,21	0,10	0,30	0,07

	EASTERN EUROPE		POLAND		RUSSIA		TURKEY	
	Means	**p-values**	**Means**	**p-values**	**Means**	**p-values**	**Means**	**p-values**
2005 and 2006	0,40	0,08	0,33	0,10	0,35	0,06	0,34	0,07
2007	0,45	0,08	0,41	0,10	0,40	0,07	0,43	0,08
2008	0,51	0,03	0,48	0,03	0,45	0,02	0,48	0,04
2009	0,46	0,07	0,41	0,07	0,41	0,07	0,41	0,09
	ROMANIA		**SLOVENIA**		**EUROPE**		**AUSTRIA**	
	Means	**p-values**	**Means**	**p-values**	**Means**	**p-values**	**Means**	**p-values**
2005 and 2006	0,13	0,23	0,06	0,24	0,42	0,04	0,37	0,05
2007	0,22	0,15	0,07	0,24	0,50	0,06	0,45	0,04
2008	0,37	0,04	0,27	0,06	0,55	0,03	0,51	0,02
2009	0,24	0,12	0,12	0,25	0,52	0,03	0,43	0,06
	FRANCE		**GERMANY**		**JAPAN**		**UNITED KINGDOM**	
	Means	**p-values**	**Means**	**p-values**	**Means**	**p-values**	**Means**	**p-values**
2005 and 2006	0,40	0,06	0,39	0,04	0,18	0,17	0,39	0,05
2007	0,49	0,07	0,48	0,04	0,10	0,31	0,48	0,05
2008	0,54	0,03	0,53	0,01	0,19	0,18	0,52	0,03
2009	0,51	0,03	0,49	0,06	0,03	0,45	0,48	0,03
	USA							
	Means	**p-values**						
2005 and 2006	0,22	0,14						
2007	0,26	0,14						
2008	0,26	0,13						
2009	0,25	0,11						

Source: computations in Matlab realized by the authors

The next step in our analysis consists in performing the test of the significance of the size of the correlations in the period before August 15th 2008 and the period after that specific date. After consulting a lot of opinions concerning the moment at which the crisis started, we found that many analysts are referring to this date. Hence, in table

2 we present the average values of the means of all the daily correlations of each country in our sample with each of the other countries for the period before this date and the period after.

As in table 1, we can observe that the p-values become smaller as we go from the period before August 15th 2008 towards the period after that moment. We consider this to be evidence of the fact that there exists contagion in these markets.

Table 2 – The average values of all the daily correlations of each country in the sample for the before (B) and after (A) periods

		CZ		HU		BU		PL		RO		SL	
		M	P	M	P	M	P	M	P	M	P	M	P
HU	B	0.5	0	0	0	0	0	0	0	0	0	0	0
	A	0.6	0	0	0	0	0	0	0	0	0	0	0
BU	B	0	0.5	0	0.5	0	0	0	0	0	0	0	0
	A	0.4	0.1	0.3	0	0	0	0	0	0	0	0	0
CR	B	0.2	0.2	0.2	0.3	0.1	0.4	0	0	0	0	0	0
	A	0.5	0	0.4	0.1	0.5	0.1	0	0	0	0	0	0
EE	B	0.6	0	0.6	0	0	0.4	0	0	0	0	0	0
	A	0.8	0	0.6	0	0.4	0	0	0	0	0	0	0
PL	B	0.5	0	0.7	0	0	0.5	0	0	0	0	0	0
	A	0.7	0	0.6	0	0.3	0	0	0	0	0	0	0
RU	B	0.5	0	0.5	0	0.1	0.1	0.5	0	0	0	0	0
	A	0.7	0	0.5	0	0.2	0	0.6	0	0	0	0	0
TU	B	0.5	0	0.6	0	0.1	0.4	0.6	0	0	0	0	0
	A	0.6	0	0.6	0	0.3	0.2	0.6	0	0	0	0	0
RO	B	0.2	0.2	0.2	0.1	0.2	0.2	0.2	0.2	0	0	0	0
	A	0.5	0	0.5	0	0.3	0.1	0.5	0	0	0	0	0
SL	B	0.1	0.4	0.1	0.4	0.1	0.4	0.1	0.3	0.2	0.2	0	0
	A	0.3	0.2	0.3	0.1	0.4	0.1	0.3	0.1	0.3	0.3	0	0
EU	B	0.5	0	0.6	0	0.1	0.1	0.6	0	0.3	0.2	0.1	0
	A	0.7	0	0.6	0	0.3	0	0.7	0	0.4	0	0.3	0
AU	B	0.5	0	0.5	0	0.1	0.1	0.6	0	0.3	0.2	0.1	0
	A	0.6	0	0.5	0	0.2	0	0.6	0	0.4	0.1	0.3	0
FR	B	0.5	0	0.5	0	0	0.2	0.6	0	0.2	0.2	0.1	0.1
	A	0.6	0	0.6	0	0.2	0	0.6	0	0.4	0	0.3	0
GR	B	0.5	0	0.6	0	0.1	0.1	0.6	0	0.2	0.2	0.1	0
	A	0.6	0	0.6	0	0.2	0	0.6	0	0.4	0	0.3	0
JP	B	0.2	0.2	0.1	0.3	0.1	0.4	0.1	0.2	0.2	0.3	0.1	0.3
	A	0.2	0.3	0.1	0.4	0.4	0	0.1	0.3	0.1	0.3	0.4	0.1

UK	B	0.5	0	0.5	0	0.1	0.1	0.6	0	0.2	0.2	0.1	0
	A	0.6	0	0.6	0	0.2	0	0.6	0	0.4	0	0.3	0
US	B	0.2	0.2	0.2	0.2	0	1	0.2	0.1	0	0	NA	NA
	A	0.2	0.1	0.3	0.1	0	0.8	0.2	0	0.1	0	0	NA

		AU		FR		GR		JP		UK	
		M	P	M	P	M	P	M	P	M	P
HU	B	0	0	0	0	0	0	0	0	0	0
	A	0	0	0	0	0	0	0	0	0	0
BU	B	0	0	0	0	0	0	0	0	0	0
	A	0	0	0	0	0	0	0	0	0	0
CR	B	0	0	0	0	0	0	0	0	0	0
	A	0	0	0	0	0	0	0	0	0	0
EE	B	0	0	0	0	0	0	0	0	0	0
	A	0	0	0	0	0	0	0	0	0	0
PL	B	0	0	0	0	0	0	0	0	0	0
	A	0	0	0	0	0	0	0	0	0	0
RU	B	0	0	0	0	0	0	0	0	0	0
	A	0	0	0	0	0	0	0	0	0	0
TU	B	0	0	0	0	0	0	0	0	0	0
	A	0	0	0	0	0	0	0	0	0	0
RO	B	0	0	0	0	0	0	0	0	0	0
	A	0	0	0	0	0	0	0	0	0	0
SL	B	0	0	0	0	0	0	0	0	0	0
	A	0	0	0	0	0	0	0	0	0	0
EU	B	0	0	0	0	0	0	0	0	0	0
	A	0	0	0	0	0	0	0	0	0	0
AU	B	0	0	0	0	0	0	0	0	0	0
	A	0	0	0	0	0	0	0	0	0	0
FR	B	0.7	0	0	0	0	0	0	0	0	0
	A	0.7	0	0	0	0	0	0	0	0	0
GR	B	0.7	0	0,9	0	0	0	0	0	0	0
	A	0.7	0	0,9	0	0	0	0	0	0	0
JP	B	0.2	0,2	0,2	0,3	0,2	0,2	0	0	0	0
	A	0.1	0,4	0,1	0,4	0	0,4	0	0	0	0
UK	B	0.7	0	0,9	0	0,8	0	0,2	0,3	0	0
	A	0.7	0	0,9	0	0,8	0	0,1	0,3	0	0
US	B	NA	NA	0,6	0	0,5	0	0,1	0,4	0,6	0
	A	NA	NA	0,6	0	0,5	0	0	0,5	0,6	0

5. Conclusions

In this paper we performed a test of contagion on 17 stock indices that include developed and emerging markets. We used the Dynamic Conditional Correlation technique in a GARCH framework to compute the daily correlations for a period starting in 2005 and ending in 2008.

We found that the correlations become more statistically significant as we go from the early stages of our sample towards the end of it. Our test takes into account the fact that the correlations can change from one day to another and it can provide powerful evidence in the support of the phenomenon of contagion.

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