Lappeenranta University of Technology

School of Business/ Department of Finance

Bachelor's Thesis

# Integration or a Greek tragedy?: How crisis spillovers affect Central and Eastern European States

Tobias Burton

0329201

Instructor:

Dr. Kashif Saleem

# Contents

## 1. Introduction

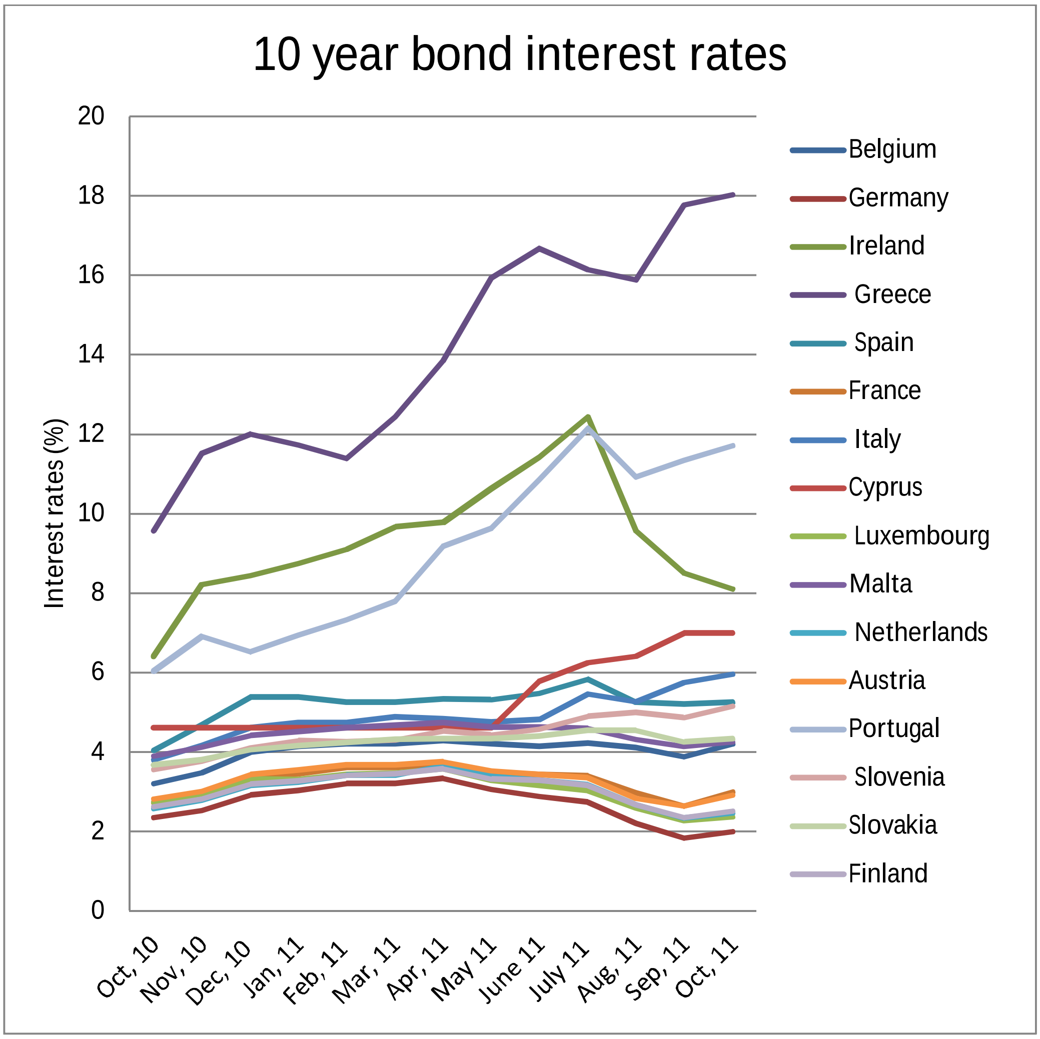
Ground-breaking work by Tobin (1958) and Markowitz (1959) proved that diversifying one's portfolio to cover an abundance of assets reduces the risk-to-reward ratio. The portfolio theory, as it is known, is based on keeping positive correlation between assets to a minimum, thus diversifying the variance unique to a particular asset away and only leaving the systemic risk (see Markowitz 1959 p. 15-19). In 1968 Grubel extended the portfolio theory to apply it to separate countries, with different currencies and economic policies, and found that risk reduction through diversification was possible (Grubel 1968 p. 1301, 1304-1309). This has been put down to the markets not being fully integrated with one another, reducing their correlation (see for instance French and Porteba 1991, p. 223-224). Bekaert and Harvey (1997) concluded that volatility in integrated markets was more linked to global factors, while market fluctuation in less integrated markets was more closely related to domestic issues (Bekaert and Harvey 1997 p. 70).

Applying a model that allows integration to vary in time, Bekaert and Harvey (1997) have discovered that markets which are unaffected by others tend to be more volatile than their highly integrated counterparts. This is attributed to a number of factors, of which Bekaert and Harvey consider four: in less integrated markets assets are concentrated and just a few stocks dictate trading, stock markets are not developed or integrated and concentrate around certain industries, there is a lack of liquidity regarding market information and the markets themselves, and general political as well as macroeconomic factors tend to increase volatility. (Bekaert and Harvey 1997 p. 58-60)

Due to these findings, as well as for other economic reasons, the past few decades have seen a push by many countries towards market liberalisation and integration. This is evident through the introduction of large scale Free Trade Agreements, such as NAFTA and Mercosur in the Americas, the allowance of foreign investments in previously private markets, and other reductions of barriers to trade throughout the world.

In Europe the process to promote economic interdependence led to the creation of the EU (Kim et al. 2005 p. 2475-2476). This huge single market currently involves 27 countries (European Union website reference 1), of which 17 have adopted and operate the single currency, the euro, which was introduced into circulation in 2002. The euro is a key part of an advanced stage of integration between European economies, with monetary policy being up to the European Central Bank (the ECB). (European Union website reference 2)

During the current financial crisis that began in 2007, without the option to devalue their currency, many Eurozone member states have seen confidence drain in their ability to repay their gilts. This can be seen by the rise in premium rates demanded on bonds issued by the Eurozone states, pictured in graph 1. The so-called PIIGS countries (Portugal, Ireland, Italy, Greece and Spain) have been seen as particularly vulnerable due to their high exposure to foreign debt compared to their Gross domestic product, high unemployment, and uncompetitive economy (The Economist website reference 1). However, a crisis that began at the periphery of Europe has since spread to cause significant turmoil throughout the markets of EU member states.




*Graph 1. Eurozone member states' 10 year bond's interest rates (source: ECB website reference 1)*

Greece in particular has been a cause for high uncertainty in the markets. One bailout loan has already been issued to the state from other EU members and the IMF, while another has been agreed on in principle (Reuters website reference 1). Even so, Greece is struggling to make repayments, with "a haircut", a write-off of some of the debt, already agreed on for Greek issued debt (Bloomberg website reference 1). These problems may have a larger economic impact on Eastern Europe.

Prior research has noted that close proximity brings about local and regional situations that increase volatility spillovers amongst neighbouring countries. As trade is mainly regional, contagion in economic crises tends to spread between countries in the same region, regardless of whether their economies complement or compete with each other, or whether they are at different stages of economic development. However, the role of trade linkages in spreading crises can be questioned. (Caporale et al. 2006 p. 376)

This study seeks to identify whether, in times of economic turbulence, local effects from a country relatively close by outweigh spillovers from a larger regional market to countries that, historically, have had low cointegration. Bulgaria, Romania, Hungary and the Czech Republic represent Eastern and Central European countries at varying proximity to Greece. The fall of the Soviet Union allowed the countries to open up their markets, and at present they are all in the process of seeking cointegration with Europe. Hungary and the Czech Republic joined the European Union in 2004, while Romania and Bulgaria joined in 2007. At present none are members of the European Monetary Union, EMU.

While previous papers have studied the transitional economies of former communist states, few have extended their research to include the current tumultuous times. With the Greek market representing local major disruptions within Europe, it can be argued that, at present, there is a unique opportunity to narrow down and pinpoint what effect the source of most of the European troubles has on countries previously behind the Iron Curtain. That is, whether possible spillovers are being emitted directly from the source, Greece, or through a proxy, the EMU markets.

The effects of Greek innovations on Bulgaria, Romania, Hungary and the Czech Republic will be compared to those emitted by EMU member states, which will represent the regional shocks. An increase in the significance of spillovers from the EMU would indicate that the countries have been successful in becoming more integrated with Europe. Whether the increase in cointegration is due to contagion, the more negative effects of the crisis spreading, will also be measured.

Specifically, the following null hypotheses will be set and examined:

1. $H_0$: The markets studied are not cointegrated enough for there to have been significant shock or volatility spillovers into Hungary, Bulgaria, Romania or the Czech Republic before the current financial crisis.

2. $H_0$: The markets studied are not cointegrated enough for there to be significant shock or volatility spillovers into Hungary, Bulgaria, Romania or the Czech Republic during the financial crisis.

3. $H_0$: Contagion of the financial crisis into Hungary, Bulgaria, Romania or the Czech Republic is not evident in possible volatility spillovers during the financial crisis.

4. $H_0$: Possible spillovers are symmetric, that is to say that the strength of the spillover will be the same, irrespective of its sign.

## 2. Literature review

While studying volatility spillovers from Japan and the USA to markets in the Pacific Basin with a GARCH-BEKK model, Ng (2000) confirmed that global and regional volatility spillovers to recently liberalised markets do happen, with the global shocks having a larger effect than the regional ones (Ng 2000 p. 230). Ng found that negative shocks generally get a bigger response than positive ones (Ng 2000 p. 221-223). However, the overall amount of volatility in the Pacific Basin that can be explained by global and regional shocks is limited. This Ng attributed to either problems with the variables used, or the possibility that the markets are affected by shocks specific to the Pacific Basin. (Ng 2000 p. 230-231)

Meanwhile, Kim et al. (2005) studied the effect an integrated EMU has had on the regions markets. The success of European integration is measured for the time period from July 1989 to May 2003. With the work of an ARMA-EGARCH model, Kim et al. found that while level of integration fluctuated throughout the early part of the 1990's cointegration increased leading up to the introduction of the final phase of the EMU process in 1999. They discovered that EMU member states have not only become more integrated with each other, but also Japan and the US. (Kim et al. 2005 p. 2500)

Baele (2004), on the other hand, used a regime switching model to conclude that for Western European markets the main period of integration came during the late 1980's and early 1990's as opposed near the launch of the euro. Baele also found evidence that spillovers from the US market are increasing (Baele 2004 p. 33).

Panayiotis and Vasila (2010) looked at companies from the six largest EU markets using a bivariate GARCH-BEKK to measure the volatility spillovers. Analysing the most traded stocks of the UK, France, Germany, Spain, Italy and Denmark between January 2002 and November 2007, the authors interpolated these results to conclude that French stocks are the most interconnected, followed by the UK, then Germany, Spain, Denmark and finally Italy.

With regards to the countries used in this study, Rockinger and Urga (2001), Kasch- Haroutoinian and Price (2001), Scheicher (2001), and Li and Majerowska (2008) examine spillover effects concerning Hungary and the Czech Republic.

In their paper, "A Time-Varying Parameter Model to Test for Predictability and Integration in the Stock Markets of Transition Economies", Rockinger and Urga introduced a model that can test whether markets do become more integrated over time without macroeconomic conditioning variables, by allowing for time-varying parameters through the Kalman filter framework (Rockinger and Urga 2001 p.73). The Kalman filter model then used a general GARCH structure to model the volatility in the residuals (Rockinger and Urga 2001 p.74). This model was then put to practical use by studying the spillovers in returns into certain Central and Eastern European markets, namely Hungary, Poland, Russia and the Czech Republic, to examine how integrated they became with more established markets between April 1994 and July 1997 (Rockinger and Urga 2001 p.76). The established markets given by the paper are the USA for global factors and the UK and Germany for local factors. The results of the paper found that for all of the given time period, the Czech market did not experience any significant spillovers from the US, while experiencing only marginally significant spillovers from the UK market. The effect of Germany fluctuated throughout the give time period, with spillovers actually becoming less significant as the sample period progresses. The Hungarian market was not influenced by spillovers from the US or the UK, while German spillovers were only significant for a brief amount of time. (Rockinger- Urga 2001 p. 79-82)

Scheicher (2001) also examined spillover linkages between Hungary, Poland and the Czech Republic stock exchanges to analyse their integration with each other between January 1995 and October 1997 (Scheicher 2001 p. 27-28). Using the Financial Times / Standard and Poor's Actuaries World Index to model global returns for the time period, Scheicher also measured the markets' integration with the rest of the world (Scheicher 2001 p. 28). The spillovers Scheicher measured with a time-varying covariance matrix, which was modelled using a Multivariate GARCH- diagonal VECH model (Scheicher 2001 p. 31). To reduce parameters, Scheicher set covariances to be constant over time. It is notable that Scheicher found no volatility spillovers from the world index into any of the markets examined. Of the studied countries, the only significant source of volatility in the Hungarian market came from their own volatility shocks in the previous lag. Scheicher also discovered that while Hungarian shocks do spill over into the Czech market in a significant manner, as in the case of Hungary, all other volatility in the Czech market was caused by the Czechs' own volatility shocks from the day before. As for spillovers in returns to other countries, the Czech Republic only received spillovers from Hungary, while Hungary received spillovers from the global market and emitted spillovers to Poland as well as to the Czech Republic. (Scheicher 2001 p. 33)

In a more recent study of integration from 2008, Li and Majerowska analysed how volatility flows between the Polish, Hungarian, Czech, German and the US stock markets (Li and Majerowska 2008 p. 248). With data covering from January 1998 to the end of December 2005, Li and Majerowska acknowledge that their time period follows on from that of Scheicher's, and encourage comparing the results of the two studies, to see how the integration has progressed (Li and Majerowska 2008 p. 250). They deploy an asymmetric Multivariate GARCH-BEKK model to analyse the spillovers in returns and volatility (Li and Majerowska 2008 p. 249). The actual volatility spillovers were analysed through the conditional covariances that were estimated (Li and Majerowska 2008 p. 254).

Li and Majerowska acquired similar results to Scheicher with regard to return spillovers, with Hungary receiving spillovers from global, regional, and the Polish markets, while emitting spillovers to Poland. The Czech market was only affected by global returns, and did not emit spillovers. The shock and volatility spillovers differed from those presented by Scheicher. The Hungarian market received shock spillovers from Poland, regional and global markets, and distributed shocks to Poland and Hungary. The Czech market received shocks from all except the regional market, while no shock spillovers were emitted. There were bidirectional volatility spillovers between Hungary, Poland and the Czech Republic, while regional spillovers were insignificant to both Hungary and the Czechs and global spillovers only affected the Czech Republic. (Li and Majerowska 2008 p. 255)

Overall it could be stated that Hungary and the Czech Republic have become more integrated, though regional spillovers remain largely insignificant.

Less has been written about Romania and Bulgaria, though Pedrescu and Stancu formed a portfolio consisting of US, UK and Romanian stock indices, and measured the residuals using the GARCH method. Analysing the period between January 2004 and May 2010, they showed that volatility behaviour of the portfolio remains largely similar to that of the US index during the recent financial crisis. (Pedrescu and Stancu 2011 p. 83)

From recent articles that include the current financial turmoil, Dimitriou et al. (2011) studied volatility spillovers between Greek, German, Spanish, Italian and Portuguese stock markets, using a diagonal multivariate GARCH-VECH model. Their time span extended from 1994 to 2009, thus capturing the effect that the financial crisis has had on the main EMU protagonists. Unsurprisingly, they found that the volatility spillovers increased post 2007, while Spain overtook Germany as the lead producer of volatility spillovers to and from other countries during the crisis period (Dimitriou et al. 2011 p. 74-75).

Whether this increase is due to extended cointegration, or to contagion by the crisis is another matter. Even defining what is cointegration and what is contagion is troublesome.

Caporale et al. (2006) have stated that contagion is difficult to identify due to it being unclear whether the spreading of financial problems is because of contagion from spillovers or because of fundamental economic similarities (Caporale et al. 2006 p. 376). They looked at volatility spillovers from emerging markets under duress during the South East Asian financial crisis of 1997, to define what sort of contagion other markets experienced. Studying the relationships of various national markets before, during and after the crisis with a GARCH-BEKK model, Caporale et al. concluded that contagion may be caused by investor behaviour and herding of investments when crises strike. They found that as a characteristic, troubled markets often become unresponsive to spillovers from other markets. In the case of the South East Asian crisis, bidirectional spillovers became unidirectional away from the troubled markets once the crisis began. (Caporale et al. 2006 p. 388-389)

Forbes and Rigobon (2002) defined contagion to be restricted to cases where comovement between previously less correlated markets only increases significantly after the shock. If the level of market cointegration was large during periods of relative tranquillity, then large mean spillovers during times of high volatility were only seen as interdependence (Forbes and Rigobon 2002 p. 2224). They argued that the conventional method of measuring contagion is biased to find significant increases in spillovers due to heteroscedasticity; larger spillovers are not out-of-scale contagion, but a natural extension to the increase in domestic volatility experienced during crises (Forbes and Rigobon 2002 p. 2249-2250). Data were then conditioned to this assumption in the model presented by Forbes and Rigobon, who then went on to find contagion to be fairly uncommon during the major financial crises of the 1980's and 1990's, with most spillovers being only interdependence (Forbes and Rigobon 2002 p. 2240-2241, 2246-2247, 2249-2250). Some studies have suggested that Forbes' and Rigobon's model may be biased towards the null hypothesis (see for instance Corsetti et al. 2005 p. 1179).

Conversely, Bekaert, Harvey and Ng (2005) defined contagion as excess correlation compared to what is expected given the conditional returns of equity indices representing the countries studied. They proposed a factor model where correlation depends on factor loadings. Here the returns of small regional markets in Europe, South East Asia and Latin America were compared with the returns of the US stock market and their own regional portfolios. (Bekaert et al. 2005 p. 39-40)

The authors then used this model to measure whether contagion existed, or whether all spillovers can be put down to cointegration. They noted that symmetric and asymmetric GARCH models provide different results, so they tested for asymmetry. Interestingly, the US was found to be asymmetric, but for Europe, Latin America and Asia the hypothesis of symmetry could not be rejected (Bekaert el al. 2005 p. 51). Using data from 1980 (1986 for some) to 1998 they discovered that cointegration might not have been as strong as has been suggested, and that contagion was almost universal in European countries during the South East Asian crisis , with Belgium being the exception (Bekaert el al. 2005 p. 59-61).

Instead of studying correlations, Tai (2007) measured the effects of contagion by introducing a dummy variable for shocks into a conditional mean equation. The dummy variable equals zero when the markets are calm, while gaining the value 1 at times of crisis. Using a GARCH- BEKK model for volatility coefficients, Tai concluded contagion to be present if the spillover shocks associated with the dummy variable are found to be significant. (Tai 2007 p. 269-270)

One final model for deriving contagion is illustrated by Baur (2003). Unlike the previous models introduced, Baur attempted to define both contagion for the mean and contagion for the volatility

(Baur 2003 p. 411-412). Similarly to Tai (2007), the paper uses a dynamic model that adds a dummy variable to signify a crisis period for both the mean and the volatility equation. Baur noted that constant correlation can lead to bias in accepting or rejecting the theory of contagion when contagion fluctuates over time. Justifications for this are threefold; first, if correlation increases during the time-period, contagion is more likely to be rejected if the crisis is at the start of the time-period and, alternatively, accepted if it is towards the end of the observed period. Second, a structural break within the sample will also lead to contagion depending on which part of the time-period the crisis is detected. Finally, if the correlation is highly cyclical, contagion may be falsely identified when the crisis coincides with one extreme of the cycle. (Baur 2003 p. 408)

## 3. Data

The data for this study comprises of six series of daily observations for Greece, Hungary, Romania, Bulgaria, Czech Republic and a pan-Emu index between January 2nd 2002, when the first tangible effect of the EMU process, the euro, came into circulation, and November 10th 2011. The total number of observations is 2573 per series. Due to concerns over the reliability of data published directly from the stock exchanges, the data acquired was published by an independent and reliable organisation, MSCI. An exception was made in the case of Romania and Bulgaria, for which MSCI data available did not span the whole of the time period reviewed. The MSCI data that was available for both countries was matched up with the data released the stock exchanges, and the equality of mean was examined using a standard t-test. Results of the t-tests can be found in Appendix 1. For both Bulgaria and Romania, the t-tests clearly failed to reject the null hypothesis of a significant difference between the means. Hence, the time series released by the stock exchanges themselves were concluded to be sufficiently similar to the MSCI series. This assumption was expanded to cover the whole of the time span observed, and led to the series produced by their respective stock exchanges being used for Romania and Bulgaria. The actual data was obtained from Thomson- Reuters Datastream, a financial information database.

To capture the effect of the current financial crisis, the data is split into two parts, one covering the pre-crisis period and the other spanning the crisis. The bankruptcy of Lehman Brothers, whose chapter 11 ignited large turmoil worldwide, shall be used as an arbitrary cut off point as to when the financial crisis began, though effects of it were evident prior to this. Thus, the two samples range from January 2nd 2002 to September 12th 2008, and from September 15th 2008 to November 10th 2011. The total number of observations amount to 1748 and 825 respectively.

To obtain the continuously compounded relative daily changes in the returns, as opposed to absolute changes in returns, the first difference of each observation is calculated using the formula

$$r_t^* = \ln\left(\frac{r_t}{r_{t-1}}\right) \qquad (1)$$

The summary statistics for the pre-crisis data are given in table 1, and include the results of the Jarque- Bera test for normality and the Augmented Dickey-Fuller test for stationarity. Similar statistics for the crisis period are presented in table 2.

| | BULGARIA | CZECH | GREECE | HUNGARY | ROMANIA | EMU |
|---|---|---|---|---|---|---|
| Observations | 1748 | 1748 | 1748 | 1748 | 1748 | 1748 |
| Mean | 0,0012 | 0,0011 | 0,0001 | 0,0002 | 0,0006 | 0,0010 |
| Median | 0,0006 | 0,0013 | 0,0003 | 0,0001 | 0,0009 | 0,0008 |
| Maximum | 0,0819 | 0,1039 | 0,0655 | 0,0789 | 0,0555 | 0,0965 |
| Minimum | -0,0828 | -0,0707 | -0,0689 | -0,0566 | -0,0821 | -0,0978 |
| Std. Dev. | 0,0132 | 0,0143 | 0,0129 | 0,0125 | 0,0161 | 0,0150 |
| Skewness | 0,0445 | -0,1196 | -0,0578 | 0,0917 | -0,2221 | -0,2114 |
| Kurtosis | 9,4636 | 6,8511 | 6,6906 | 6,1455 | 4,1312 | 7,6473 |
| Jarque-Bera | 3043,449 | 1084,371 | 993,022 | 723,064 | 107,573 | 1586,019 |
| JB p-value | 0,000 | 0,000 | 0,000 | 0,000 | 0,000 | 0,000 |
| Augmented D-F | -37,201 | -40,621 | -43,785 | -40,054 | -40,497 | -37,174 |
| ADF p-value | 0,000 | 0,000 | 0,000 | 0,000 | 0,000 | 0,000 |

*Table 1. Summary statistics of the time series pre-crisis*

| | BULGARIA | CZECH | GREECE | HUNGARY | ROMANIA | EMU |
|---|---|---|---|---|---|---|
| Observations | 825 | 825 | 825 | 825 | 825 | 825 |
| Mean | -0,0013 | -0,0002 | -0,0002 | -0,0021 | -0,0007 | -0,0006 |
| Median | 0,0000 | 0,0006 | 0,0000 | -0,0005 | -0,0002 | 0,0004 |
| Maximum | 0,0729 | 0,1675 | 0,1009 | 0,1596 | 0,1734 | 0,1134 |
| Minimum | -0,1137 | -0,1569 | -0,0811 | -0,0995 | -0,1998 | -0,1340 |
| Std. Dev. | 0,0168 | 0,0215 | 0,0186 | 0,0281 | 0,0307 | 0,0226 |
| Skewness | -1,0123 | -0,3952 | 0,0736 | 0,2908 | -0,0394 | -0,6573 |
| Kurtosis | 10,9210 | 15,6147 | 7,1379 | 5,2819 | 8,4327 | 8,8724 |
| Jarque-Bera | 2297,688 | 5491,575 | 589,323 | 190,623 | 1014,753 | 1244,838 |
| JB p-value | 0,000 | 0,000 | 0,000 | 0,000 | 0,000 | 0,000 |
| Augmented D-F | -24,823 | -22,292 | -22,346 | -27,882 | -21,685 | -26,403 |
| ADF p-value | 0,000 | 0,000 | 0,000 | 0,000 | 0,000 | 0,000 |

*Table 2. Summary statistics of the time series during the crisis*

Before the crisis all markets exhibit a positive means, indicating that the markets are growing. Consistent with financial theory, the less risky markets (Greece and Hungary) tend to have lower means, though this did not apply at the other end of the spectrum, where the market with the highest fluctuations (Romania) is not the one with the highest returns (Bulgaria).

Once the crisis begins the means of the continuously compounded returns turn negative for all markets. Bulgaria experiences the largest fluctuation in mean, which is surprising given that it has one of the lowest standard deviations of the series both before and during the crisis. Another surprising result from the statistics covering the crisis period is the positive median of both the Czech Republic and the EMU index. The difference between the means and the medians of these markets signifies that while daily returns have largely been positive, a few large negative outliers have pushed the overall mean of the markets to be negative. This is consistent with the theory that the distributions of financial series have "fat tails".

All series are stationary according to the Augmented Dickey-Fuller test, which is to be expected considering that the first difference of returns are being used. The Jarque- Bera test indicates that none of the series are normally distributed, with excessive kurtosis evident. This is commonplace with time series data (Brooks 2008 p. 162). The correlations between the series prior to the crisis are given in table 3 and for the crisis period in table 4.

| | BULGARIA | CZECH | GREECE | HUNGARY | ROMANIA | EMU |
|---|---|---|---|---|---|---|
| BULGARIA | 1,000 | 0,036 | 0,043 | 0,080 | 0,028 | 0,082 |
| CZECH | 0,036 | 1,000 | 0,406 | 0,384 | 0,484 | 0,192 |
| GREECE | 0,043 | 0,406 | 1,000 | 0,523 | 0,437 | 0,186 |
| HUNGARY | 0,080 | 0,384 | 0,523 | 1,000 | 0,388 | 0,234 |
| ROMANIA | 0,028 | 0,484 | 0,437 | 0,388 | 1,000 | 0,201 |
| EMU | 0,082 | 0,192 | 0,186 | 0,234 | 0,201 | 1,000 |

*Table 3. The correlations between the series pre-crisis*

| | BULGARIA | CZECH | GREECE | HUNGARY | ROMANIA | EMU |
|---|---|---|---|---|---|---|
| BULGARIA | 1,000 | 0,385 | 0,280 | 0,218 | 0,266 | 0,435 |
| CZECH | 0,385 | 1,000 | 0,649 | 0,470 | 0,612 | 0,599 |
| GREECE | 0,280 | 0,649 | 1,000 | 0,559 | 0,718 | 0,565 |
| HUNGARY | 0,218 | 0,470 | 0,559 | 1,000 | 0,463 | 0,459 |
| ROMANIA | 0,266 | 0,612 | 0,718 | 0,463 | 1,000 | 0,575 |
| EMU | 0,435 | 0,599 | 0,565 | 0,459 | 0,575 | 1,000 |

*Table 4. The correlations between the series during the crisis*

Correlations preceding the crisis are generally weak but positive. It is noticeable how the Bulgarian market is largely unaffected by the other series, while the EMU index is also surprisingly uncorrelated with other countries. The only correlation above 0.5 is between Greece and Hungary. Overall, Greece is much more highly correlated with the Eastern European series than the EMU index is, leading to expectations that possible pre-crisis spillovers may be stronger from Greece.

Once the crisis starts correlations rise dramatically for all markets. Correlation with the EMU index increases significantly, though Greece remains more highly correlated of the two with all markets except Bulgaria.

Additionally in this paper to test for heteroscedasticity and autocorrelation simple linear regressions are run for all of the countries being examined

$$y_t = \alpha + \beta x_t + u_t \tag{2}$$

where the independent variable is Greece and the dependent variable is, in turn, Bulgaria, Romania, Czech Republic and Hungary. White's test for heteroscedasticity and the Breusch-Godfrey serial correlation LM test confirm that all regressions are heteroscedastic and possess autocorrelation. These results allow for the examination of volatility spillovers, which is what this thesis sets out to do.

In this study a bivariate GARCH-BEKK, introduced and justified in the following section, is employed to discover the volatility transmissions in the time series. Using WinRats 6 software, four bivariate models involving Greece with Bulgaria, Greece with Romania, Greece with Hungary, and Greece with the Czech Republic are run for the pre-crisis and then the crisis periods, after which the Greek variable is switched with the EMU variable and the models are run again. This amounts to a total of 16 bivariate GARCH-BEKK models being run.

## 4. Methodology

The GARCH-BEKK model recognizes that volatility and correlations are not constant, but fluctuate over time. Normally, if $\sigma^2$ is the variance of a variable on day *n* then it can be estimated on day *n-1* through

$$\sigma_t^2 = \frac{1}{n-1}\sum_{i=1}^{n}(u_{t-i} - \bar{u})^2 \qquad (3)$$

where $n$ is the number of observations, and $\bar{u}$ is the mean of the $u_i$'s. (Hull 2000 p. 369)

This, however, assumes variance to be constant over all observations, which empirically we find not to be true for most financial time series data. The volatility of observations tends to fluctuate over time, with pointed features such as leptokurtosis, where the volatility distribution of returns tends to show higher kurtosis and fatter tails than the Bell curve, volatility clustering, where higher volatility has a habit of following large fluctuations in returns, and leverage effects, where negative shocks tend to have a larger effect than positive shocks on volatility, common in financial data (Brooks 2008 p. 380). Thus it desirable to give the various observations separate weights, with the most recent observations emphasized. A model such as

$$\sigma_t^2 = \sum_{i=1}^{n}\alpha u_{t-i}^2 \qquad (4)$$

would satisfy this. Here $\alpha$ is the weight given to each of the observations at their respective lags. Assigning a weight for the volatility average of the whole sample, the model would take the form

$$\sigma_t^2 = \upsilon V + \sum_{i=1}^{n}\alpha u_{t-i}^2 \qquad (5)$$

Here V is the long term average volatility and $\upsilon$ the weight given to it. (See Hull 2000 p.370)

This is the Autoregressive Conditional Heteroskedastic (ARCH) model introduced by Engle in 1982. The variance is divided into two parts; the first is constant and unconditional on the past $(\upsilon V)$ while the second is nonconstant and conditional on the past values $(\alpha u_{t-i}^2)$(Engle 1982 p. 987). It is worth noting that the weights, $\upsilon$ and $\alpha$ must sum up to unity

$$\upsilon + \alpha = 1$$

The conditional variance, $\sigma_t^2$, is frequently noted as $h_t$ in literature (Brooks 2008 p. 388). Also as $\upsilon V$ is constant it can be abridged to $\omega$, so that, a one lag ARCH (1) model, for instance, can be rewritten as

$$h_t = \omega + \alpha u_{t-1}^2 \tag{6}$$

Here only the past value of the previous lag is included. In theory, previous moments all the way up to lag $q$ could be included in the model, with the weight assigned to each lag decaying towards the older observations. Difficulty in distinguishing the correct number of lags for an ARCH ($q$) model, the fact that a large number of lags could make the model less parsimonious, and risk of breaching non-negativity constraints lead to the development of the Generalised ARCH, or GARCH, model (Brooks 2008 p. 391-392). Presented by Bollerslev in 1986, the GARCH model addresses these issues by including the weighted past estimates of the conditional variances (Bollerslev 1986 p. 309). Thus a GARCH (1, 1) model would be

$$h_t = \omega + \alpha u_{t-1}^2 + \beta h_{t-1}^2 \tag{7}$$

where $\beta$ is the weight given to $h_{t-1}^2$ , the conditional variance estimate from the previous lag (Brooks 2008 p. 392). Given that

$$h_{t-1} = \omega + \alpha u_{t-2}^2 + \beta h_{t-2}^2 \tag{8}$$

$\beta h_{t-1}^2$ contains all the information of past $h_t$'s, and $\beta$ can be seen as a decay rate of the relative significance of the lagged $u_i$'s (Hull 2000 p. 373). A suitable number of lags for the GARCH model can be obtained using various information criteria, such as AIC or HQIC, but generally a GARCH (1, 1) model will be enough to identify volatility clusters (Brooks 2008 p. 395).

Obviously the assigned weights still have to add up to one (Hull 2000 p. 372).

$$\upsilon + \alpha + \beta = 1$$

In addition, a zero or negative constant unconditional variance would make little sense, so stationarity in variance

$$\alpha + \beta < 1$$

is required for the long run average volatility to be defined (Brooks 2008 p. 394).

The model specified so far is a univariate model, where variation in a variable's volatility through time is estimated on its own past values, independently of all other variables. As a model measuring volatility spillovers between two or more markets is needed to study the extent of cointegration between these countries, some model connecting the isolated time series is required (Brooks 2008 p. 428). Rockinger and Urga (2001), for instance, used a model that allowed time-varying parameters on top of a univariate GARCH (1, 1) model. More generally though, a multivariate GARCH model, which allows for the time-varying covariances between the series, is used.

Various Multivariate GARCH (or MGARCH) models exist, with the VECH, Diagonal VECH and BEKK models being among the most popular (Kroner and Ng 1998 p. 817). A basic VECH (1, 1) model can be described as

$$VECH(H_t) = C + AVECH(u_{t-1}u'_{t-1}) + GVECH(H_{t-1}) \quad (9)$$

Where $VECH(*)$ is an operator that takes each column in a lower triangular portion of a *N x N* sized matrix, and stacks them to make a corresponding *N(N+1)/2 x 1* sized vector (Bauwens et al. 2006 p. 82). Thus, $VECH(H_t)$ is the lower triangular portion of $H_t$, a variance-covariance matrix of all $h_t$'s, stacked as a vector. $C$ denotes a *N(N+1)/2 x 1* parameter vector, while $A$ and $G$ are $[N(N+1)/2]^2$ parameter matrices that are multiplied with vectors of lagged conditional residuals and past values $H_t$ respectively. (Brooks 2008 p. 432-433)

Conditional variances and conditional covariances depending on all lagged conditional variances and conditional covariances for all variables, as well as lagged square errors and error cross-products, mean that the amount of parameters required quickly explodes as the amount of variables increases (Brooks 2008 p. 433-434). The diagonal VECH model attempts to improve the feasibility of large scale models by assuming that the $A$ and $G$ matrices are diagonal, in other words, for both matrices, the model only incorporates the variance values on the diagonal axis and reduces all covariance values to 0. The method used by Scheicher (2001) was not unlike this. This reduction of parameters leaves the first order model as

$$h_{ijt} = \omega_{ij} + \alpha_{ij} u_{it-1} u_{jt-1} + \beta_{ij} h_{ijt-1} \qquad \forall\ i,j = 1, \dots, N \quad (10)$$

with $\omega_{ij}$, $\alpha_{ij}$ and $\beta_{ij}$ denoting the remaining variance parameters. (Brooks 2008 p. 434)

The VECH model also requires a positive definite covariance matrix. That is to say that the variance values on the diagonal axis need to be positive, and the covariance values need to be symmetrical about the axis. While this makes sense from a mathematical standpoint, models that are estimated through a non-linear optimisation method, such as the GARCH-VECH, might not yield positive definite matrices. Whether the matrix is positive definite is hard to verify, which leads to the requirement of making strong assumptions that the model is positive definite for it to be estimated . (Brooks 2008 p. 434-435; Engle and Kroner 1995 p. 126; Bauwens et al. 2006 p. 83)
In 1995 Engle and Kroner presented the multivariate GARCH-BEKK model, which assures positive definiteness by transforming $A$ and $G$ matrices into quadratic form, given that the matrix has a positive eigenvalue (Kroner and Ng 1998 p. 821; Simon and Blume 1994 p. 626). A BEKK (1, 1) model is as follows

$$H_t = C'C + A' u_{t-1} u'_{t-1} A + G' H_{t-1} G \qquad (11)$$

where $A$ and $G$ are N x N sized parameter matrices, and $C$ is a lower triangular parameter matrix (Engle and Kroner 1995 p. 127). As well as addressing the positive definite issue, the BEKK model also has slightly fewer parameters compared to the VECH model, although large estimations are hard to make as the model on the whole still requires $(5/2)N^2 + (N/2)$ parameters (Engle and Kroner 1995 p. 127; Kroner and Ng 1998 p. 821).

In this thesis the extent of the spillovers from Greece and PAN EMU to Romania, Bulgaria, Hungary, and the Czech Republic are studied. As linkages between Romania, Bulgaria, Hungary, and the Czech Republic themselves are not essential to the study, a bivariate model is sufficient. This allows the use of a GARCH-BEKK model, as the amount of parameters is tolerable.

Turning attention to the conditional mean equation, one model type that allows for the study on how returns of one country affects the mean coefficient of another are the Vector Autoregressive

(VAR) models. A bivariate VAR model has two dependent variables, which depend on past terms of the other dependent variable as well as their own lags and errors terms. The bivariate VAR (1) model, which will be used in this paper, is given as

$$y_{1t} = \beta_{10} + \beta_{11}y_{1t-1} + \alpha_{11}y_{2t-1} + u_{1t} \qquad u_t|I_{t-1} \sim N(0, H_t) \qquad (12)$$

$$y_{2t} = \beta_{20} + \beta_{21}y_{2t-1} + \alpha_{21}y_{1t-1} + u_{2t}$$

where in this case $y_{1t}$ represents the daily returns for a particular country. To re-emphasise, these returns depend on the past terms of $y_{1t}$ and $y_{2t}$, the returns variable for another country. Reciprocally, $y_{2t}$ also depends on the same variables, thus enabling the study of return spillovers to both countries. The paper will analyse return spillovers from Greece and the EMU index. $\beta_{10}$ and $\beta_{20}$ are both constants. (Brooks 2008 p. 290)

As mentioned above, the effects of past positive and negative innovations on volatility may be asymmetric. That is to say that a negative shock is likely to induce higher volatility than a positive shock. Reasons for this can vary, but leverage effects, in which a negative shock to a firm's value increases the debt to equity ratio, making the remaining equity seem more risky, possibly constitute one of the reasons (Brooks 2008 p. 404). As standard GARCH models do not distinguish between positive and negative shocks, an additional quadratic form will be added to the BEKK model in this study, a form which depends on the outer product of the vector of negative shocks, as per Kroner and Ng (1998 p. 836).

$$H_t = C'C + A'u_{t-1}u'_{t-1}A + G'H_{t-1}G + D'\eta'_{t-1}\eta_{t-1}D \qquad (13)$$

Now D is a 2 x 2 matrix for $\eta$'s, errors that only acquire their value if negative. In other words, $\eta_t$ will be defined as $u_t$ only if it is negative, otherwise taking the value 0, in similar manner to a dummy variable (Li and Majerowska 2008 p. 253).

The bivariate GARCH-BEKK (1, 1) model used will obtain the dimensions

$$H_t = \begin{bmatrix} c_{11} & 0 \\ c_{21} & c_{22} \end{bmatrix} + \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}' \begin{bmatrix} u_{1,t-1}^2 & u_{1,t-1}u_{2,t-1} \\ u_{2,t-1}u_{1,t-1} & u_{2,t-1}^2 \end{bmatrix} \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} +$$

$$\begin{bmatrix} g_{11} & g_{12} \\ g_{21} & g_{22} \end{bmatrix}' H_{t-1} \begin{bmatrix} g_{11} & g_{12} \\ g_{21} & g_{22} \end{bmatrix} + \begin{bmatrix} d_{11} & d_{12} \\ d_{21} & d_{22} \end{bmatrix}' \begin{bmatrix} \eta_{1,t-1}^2 & \eta_{1,t-1}\eta_{2,t-1} \\ \eta_{2,t-1}\eta_{1,t-1} & \eta_{2,t-1}^2 \end{bmatrix} \begin{bmatrix} d_{11,} & d_{12} \\ d_{21} & d_{22} \end{bmatrix} \quad (14)$$

In the matrices, the $a$'s represent the ARCH effect, with the diagonal axis $a$'s indicating the effect of the country's own past shocks, and $a$'s off the diagonal axis representing the spillover of shocks between series. The $g$'s represent the GARCH effect where, similarly to $a$'s, diagonal axis $g$'s show the effects of past volatility within the series, while off-diagonal $g$'s express the effects that past volatilities from other series are transmitting (Li and Majerowska 2008 p. 249). The diagonal $d$'s will measure the effect of the country's own past negative shocks, while off-diagonal $d$'s will show the response to negative shocks in other markets (Li and Majerowska 2008 p. 254).The individual $h$'s acquire their value from

$$h_{11} = c_{11} + a_{11}^2 u_{1,t-1}^2 + 2a_{11}a_{12}u_{1,t-1}u_{2,t-1}a_{21}^2 u_{2,t-1}^2 + g_{11}^2 h_{11,t-1} + 2g_{11}g_{21}h_{12,t-1} + g_{21}^2 h_{22,t-1} + d_{11}^2 \eta_{1,t-1}^2 + 2d_{11}d_{12}\eta_{1,t-1}\eta_{2,t-1}d_{21}^2\eta_{2,t-1}^2 \tag{15}$$

$$h_{12} = c_{21} + a_{11}a_{12}u_{1,t-1}^2 + (a_{21}a_{12} + a_{11}a_{22})u_{1,t-1}u_{2,t-1} + a_{21}a_{22}u_{2,t-1}^2 + g_{11}g_{12}h_{11,t-1} + (g_{21}g_{12} + g_{11}g_{22})h_{12,t-1} + g_{21}g_{22}h_{22,t-1} + d_{11}d_{12}\eta_{1,t-1}^2 + (d_{21}d_{12} + d_{11}d_{22})\eta_{1,t-1}\eta_{2,t-1} + d_{21}d_{22}\eta_{2,t-1}^2 \tag{16}$$

$$h_{22} = c_{22} + a_{12}^2 u_{1,t-1}^2 + 2a_{12}a_{22}u_{1,t-1}u_{2,t-1}a_{22}^2 u_{2,t-1}^2 + g_{12}^2 h_{11,t-1} + 2g_{12}g_{22}h_{12,t-1} + g_{22}^2 h_{22,t-1} + d_{12}^2 \eta_{1,t-1}^2 + 2d_{12}d_{22}\eta_{1,t-1}\eta_{2,t-1}d_{22}^2\eta_{2,t-1}^2 \tag{17}$$

(Engle and Kroner 1995 p. 127; Karanasos and Kim 2005 p. 18-19)

How the parameters are estimated is explained below, however, it is difficult to make any inferences from the $h$'s, and their net effects on variances and covariances are not obvious (Li and Majerowska 2008 p. 254). Like Li & Majerowska's (2008) paper, this study will use the conditional covariance estimates, the off-diagonal $a$'s and $g$'s, to measure the shock and volatility transmissions.

## 4.1 Estimating GARCH-BEKK

As ARCH and GARCH models, and their extensions, allow for fluctuation in the variance, estimating them using the Ordinary Least Squares method, which minimises the residual sum of squares, is not desirable. This is mainly because the residual sum of squares are calculated simply using the conditional mean equation, while ignoring the conditional variance (Brooks 2008 p. 395). Instead, the maximum likelihood method is used. Maximum likelihood attempts to find the values that, given the data, have the highest probability of being the correct for the parameters. As such this estimation method can also be employed in the case of a GARCH-BEKK. The most likely parameter values are obtained by first creating a logarithmic likelihood function of the data, then running the regression and making some initial predictions as to where variance parameters may be, before differentiating the likelihood function with regards to the parameters until the iterations converge around the maximum likelihood estimates (Brooks 2008 p. 398). The parameters of a GARCH-BEKK model can be acquired by maximising the log likelihood function

$$l(\theta) = -\frac{TN}{2}\log 2\pi - \frac{1}{2}\sum_{t=1}^{T}(\log |H_t| + u_t' H_t^{-1} u_t) \tag{18}$$

where $l(\theta)$ indicates that this is a likelihood function for all unknown parameters, $\theta$, that are estimated. $N$ is the number of separate time series in the model, while $T$ denotes the number of observations (Brooks 2008 p. 435). Maximising the function can be accomplished using various optimisation methods that may give out different results for the coefficients and standard errors (Brooks 2008 p. 398). The optimisation method used in the study is the Broyden, Fletcher, Goldfarb, Shanno (BFGS) method, which is the default estimation method in WinRats (Estima 2004 p. 408).

## 4.2 Diagnostic tests

The Ljung-Box test measures the overall autocorrelation dependence within the series. It does this by taking a series of lags and jointly testing whether their autocorrelation significantly differs from zero. This means that while individual autocorrelation coefficients may be insignificant, the series, which contains the coefficients may be jointly significant, and vice versa.

$$Q^* = T(T+2)\sum_{k=1}^{m}\frac{\hat{\tau}_k^2}{T-k} \quad \sim\chi_m^2 \tag{19}$$

Here $Q^*$ is the Ljung-Box Q-statistic denoting the overall value, of the term. Its significance is determined by comparing it to the corresponding critical values of a $\chi^2$- distribution, given the degrees of freedom. $T$ denotes the sample size, and $m$ the maximum lag length. $\hat{\tau}_k^2$ signifies the squared autocorrelation of lag $k$. (Brooks 2008, p. 209-210)

In this paper the Ljung-Box test will be used with both a series of 12 lags and a series of 24 lags.

## 4.3 Testing for contagion

While examining contagion in the mean is likely to lead to some interesting results over whether the crisis has spread into the markets in terms of returns, analysing volatility contagion is more apt for observing which market fluctuations are due to the current turmoil.

Baur's paper applies the following volatility equation:

$$h_{1t} = \omega + \alpha_0 u_{t-1}^2 + \beta_0 h_{t-1} + d_1 r_{2,t-1}^2 + d_2 r_{2,t-1}^2 D_{Crisis,t-1} \tag{20}$$

where, on top of past shocks, volatility estimates and constant variance, the volatility estimate for a variable, $h_{1t}$, depends on volatility spillovers from another series. The general spillovers observed throughout the series are denoted by $d_1 r_{2,t-1}^2$. The final regressor reveals spillovers in crisis, and will assume the value 0 in times of calm. (Baur 2003 p. 413)

Following Baur's (2003) definition of volatility contagion as the amount of change in crisis volatility spillovers when compared to ubiquitous spillovers in calmer times, the study will identify possible excess crisis spillovers as contagion, when compared to their pre-crisis counterpart (Baur 2003 p. 413). Moreover, since this paper splits the overall sample into pre-crisis and crisis periods, determining the presence of contagion will be done by simply comparing spillovers of the two periods. While such a definition may not be ideal, as it ignores possible cointegration during the crisis, Baur's view on what constitutes contagion is clear and easily measurable.

The null hypotheses will now be defined as:

1. $H_0$: $a_{12(pre\text{-}crisis)} = g_{12(pre\text{-}crisis)} = 0$
2. $H_0$: $a_{12(crisis)} = g_{12(crisis)} = 0$
3. a) $H_0$: $a_{12(pre\text{-}crisis)} \geq a_{12(crisis)}$

   b) $H_0$: $g_{12\ (pre\text{-}crisis)} \geq g_{12\ (crisis)}$
4. $H_0$: $d_{12\ (pre\text{-}crisis)} = d_{12\ (crisis)} = 0$

Given a five percent risk level.

## 5. Results

The following outputs represent spillovers from Greece and the EMU index to Bulgaria, Romania, Hungary and the Czech Republic. The subscript $g$ indicates spillovers from Greece and the subscript $EMU$ shows spillovers from The EMU index. The p-value directly below each figure indicates whether the figure significantly differs from zero. Figures that are significant at 5 per cent risk level are indicated in italics and bold and have an asterisk after them. Full results for the GARCH-BEKK estimations can be found in Appendix 2, though no inferences will be made from them. How the countries are linked to Greece and the EMU index in terms of returns is presented below in table 5.

| Pre-crisis | Czech | Hungary | Bulgaria | Romania | Pre-crisis | Czech | Hungary | Bulgaria | Romania |
|---|---|---|---|---|---|---|---|---|---|
| $y_g$ | -0,0134 | -0,0080 | *0,0366** | *0,0614** | $y_{EMU}$ | -0,0318 | -0,0021 | 0,0300 | *0,0450** |
| p-value | 0,5712 | 0,7765 | 0,0244 | 0,0074 | p-value | 0,1886 | 0,9446 | 0,1268 | 0,0389 |
| Crisis | Czech | Hungary | Bulgaria | Romania | Crisis | Czech | Hungary | Bulgaria | Romania |
| $y_g$ | 0,0214 | 0,0069 | 0,0069 | 0,0114 | $y_{EMU}$ | *0,1192** | 0,0186 | *0,1097** | *0,1915** |
| p-value | 0,2011 | 0,8245 | 0,4859 | 0,5353 | p-value | 0,0009 | 0,7923 | 0,0000 | 0,0000 |

*Table 5. Returns of the constant component of the mean equation*

Prior to the crisis there were significantly positive return spillovers from Greece to Romania and Bulgaria, as well as from the EMU index to Romania. The means of all the other markets were unaffected by what was happening in Greece and the eurozone between January 2002 and August 2008. Once the crisis began spillovers from EMU index became much more significant. Spillovers from Greece are no longer significant as the returns of Bulgaria and Romania are led only by the returns of the EMU market. The index now also sends positive spillovers into the Czech Republic, while the Hungarian market still remains unaffected by anything.

The fluctuations in volatility, more essential to this study, are shown in table 6. In table 6 $c$ signifies the constant term, $a$ represents the shock spillovers, the ARCH effect, and $g$ indicates the volatility spillovers, the GARCH effect. $d$ shows the asymmetric effect of negative shock spillovers, while $Q^{*}12$ and $Q^{*}24$ give the Ljung-Box Q-statistic for 12 lags and 24 lags respectively. The number in brackets after the Q-statistic denotes which series the estimates are for. Llklhood is the overall Log likelihood sum of the regression.

| Pre-crisis | Czech | Hungary | Bulgaria | Romania | Pre-crisis | Czech | Hungary | Bulgaria | Romania |
|---|---|---|---|---|---|---|---|---|---|
| $c_g$ | 0,0028* | 0,0017 | -0,0002 | 0,0003 | $c_{EMU}$ | 0,0022* | -0,0019* | 0,0002 | 0,0000 |
| p-value | 0,0000 | 0,1003 | 0,5135 | 0,4927 | p-value | 0,0000 | 0,0104 | 0,5425 | 0,9037 |
| $a_g$ | -0,0852* | -0,1254* | -0,0157 | 0,0251 | $a_{EMU}$ | -0,0016 | -0,1150* | -0,0654 | -0,0379 |
| p-value | 0,0083 | 0,0014 | 0,4068 | 0,3144 | p-value | 0,9738 | 0,0001 | 0,0964 | 0,0955 |
| $g_g$ | 0,0152 | 0,0397* | 0,0071 | -0,0135 | $g_{EMU}$ | 0,0093 | 0,0112 | -0,0241 | -0,0081 |
| p-value | 0,2708 | 0,0213 | 0,3614 | 0,2334 | p-value | 0,3460 | 0,2755 | 0,0750 | 0,2511 |
| $d_g$ | 0,0185 | -0,0675 | -0,0138 | 0,0774 | $d_{EMU}$ | -0,0096 | 0,0680 | 0,1306* | -0,0628 |
| p-value | 0,6909 | 0,1659 | 0,6014 | 0,0986 | p-value | 0,8260 | 0,1529 | 0,0207 | 0,0686 |
| $Q^*12(1)$ | 11,6137 | 11,3720 | 12,0508 | 12,2504 | $Q^*12(1)$ | 16,6239 | 16,6269 | 16,6400 | 17,1874 |
| p-value | 0,4772 | 0,4973 | 0,4416 | 0,4258 | p-value | 0,1643 | 0,1642 | 0,1636 | 0,1427 |
| $Q^*24(1)$ | 28,4099 | 28,3178 | 29,2888 | 29,3866 | $Q^*24(1)$ | 22,0768 | 22,2167 | 22,1626 | 22,5136 |
| p-value | 0,2431 | 0,2469 | 0,2095 | 0,2059 | p-value | 0,5747 | 0,5663 | 0,5696 | 0,5486 |
| $Q^*12(2)$ | 13,4827 | 13,1892 | 22,2061* | 23,6712* | $Q^*12(2)$ | 14,3782 | 13,6159 | 20,0178 | 23,9695* |
| p-value | 0,3350 | 0,3554 | 0,0353 | 0,0225 | p-value | 0,2772 | 0,3259 | 0,0668 | 0,0205 |
| $Q^*24(2)$ | 30,0898 | 23,3246 | 29,6418* | 40,5075* | $Q^*24(2)$ | 30,2464 | 23,9799 | 28,6805 | 41,1501* |
| p-value | 0,1818 | 0,5007 | 0,1969 | 0,0189 | p-value | 0,1767 | 0,4627 | 0,2324 | 0,0160 |
| Llklhood | 10567,57 | 10281,27 | 10750,94 | 10449,12 | Llklhood | 10780,67 | 10563,36 | 10955,50 | 10639,43 |
| Crisis | Czech | Hungary | Bulgaria | Romania | Crisis | Czech | Hungary | Bulgaria | Romania |
| $c_g$ | 0,0010 | -0,0023* | 0,0009 | -0,0023* | $c_{EMU}$ | -0,0010 | 0,0029* | 0,0001 | 0,0004 |
| p-value | 0,3231 | 0,0298 | 0,1523 | 0,0000 | p-value | 0,1984 | 0,0001 | 0,9179 | 0,4326 |
| $a_g$ | 0,0336 | -0,0127 | 0,0117 | -0,0137 | $a_{EMU}$ | 0,1424 | 0,0726 | 0,0769* | 0,0285 |
| p-value | 0,1537 | 0,7211 | 0,3390 | 0,5758 | p-value | 0,0014 | 0,5227 | 0,0000 | 0,5410 |
| $g_g$ | -0,0127 | 0,0575* | -0,0096 | 0,0351* | $g_{EMU}$ | -0,0133 | -0,0104 | 0,0021 | -0,0537* |
| p-value | 0,5224 | 0,0003 | 0,3231 | 0,0039 | p-value | 0,7484 | 0,7418 | 0,8351 | 0,0000 |
| $d_g$ | 0,0543 | 0,0090 | -0,0031 | 0,0413 | $d_{EMU}$ | 0,3152* | 0,3551* | -0,0112 | 0,2601* |
| p-value | 0,0874 | 0,8524 | 0,8656 | 0,2624 | p-value | 0,0000 | 0,0027 | 0,7249 | 0,0000 |
| $Q^*12(1)$ | 13,9948 | 13,4154 | 12,0303 | 12,7437 | $Q^*12(1)$ | 8,7126 | 9,5166 | 7,3563 | 10,4039 |
| p-value | 0,3010 | 0,3396 | 0,4433 | 0,3879 | p-value | 0,7273 | 0,6583 | 0,8332 | 0,5806 |
| $Q^*24(1)$ | 25,4714 | 24,0488 | 24,2160 | 23,4715 | $Q^*24(1)$ | 16,8010 | 17,7144 | 16,3519 | 17,0862 |
| p-value | 0,3805 | 0,4588 | 0,4493 | 0,4921 | p-value | 0,8570 | 0,8166 | 0,8750 | 0,8450 |
| $Q^*12(2)$ | 12,7242 | 14,5090 | 36,4111* | 9,7688 | $Q^*12(2)$ | 12,0416 | 16,6020 | 40,0655* | 10,5357 |
| p-value | 0,3894 | 0,2694 | 0,0003 | 0,6362 | p-value | 0,4423 | 0,1652 | 0,0001 | 0,5691 |
| $Q^*24(2)$ | 21,1228 | 25,7751 | 42,5847* | 26,5645 | $Q^*24(2)$ | 21,1174 | 27,4384 | 46,4924* | 22,9356 |
| p-value | 0,6315 | 0,3647 | 0,0111 | 0,3252 | p-value | 0,6318 | 0,2844 | 0,0039 | 0,5236 |
| Llklhood | 4189,74 | 3765,62 | 4358,93 | 4063,26 | Llklhood | 4751,45 | 4420,50 | 4849,46 | 4575,72 |

*Table 6. Volatility spillovers and diagnostic tests*

The results are something of a mixed bag. Opposite to the returns spillovers, before the crisis erupted Greece had significant negative shock spillovers to Hungary and the Czech Republic, meaning that these markets were actually calmed by an increase of turbulence in Greece while a reduction in Greek shocks actually increased volatility in Hungary and the Czech Republic, and significant positive volatility spillovers to Hungary. Romania and Bulgaria remained ambivalent to Greek spillovers.

After the collapse of Lehman Brothers, Greek shock spillovers lost all significance, but there are significant positive volatility spillovers into Romania on top of the volatility spillovers into Hungary, which also gain in strength.

Up until August 2008 shock and volatility spillovers from the EMU index were largely insignificant, with significant negative shock spillovers into Hungary being the exception. As with the returns spillovers the influence of EMU spillovers increased once the turmoil begins, with significant positive shock spillovers being emitted into Bulgaria and the Czech Republic. The previously significant spillovers into Hungary became insignificant. There were also significant negative volatility spillovers from the eurozone into Romania.

The spillovers from Greece were all symmetric pre-crisis, and remained so after the bankruptcy of Lehman Brothers. This is surprising, since it could be assumed that negative shocks are even more likely to get an asymmetric response during financial crises. The responses to spillovers from the EMU index seem more conventional, with significantly positive asymmetricity, meaning that leverage effects are present, in Bulgaria pre-crisis. The roles are reversed in the financial crisis, with all markets except Bulgaria showing a significant positive asymmetric response to spillovers from the eurozone.

With most spillovers insignificant, the remaining being significantly positive or negative seemingly by happenstance, integration still seems to be an ongoing process in Central and Eastern Europe. On the whole the countries were more integrated with Greece than the eurozone before the crisis, though the importance of the EMU index matched that of Greece once trouble broke out.

Turning attention to the diagnostic tests, The Ljung- Box Q-statistic seems to indicate that by and large the model is acceptable for Hungary and the Czech Republic. More worryingly however, the Q-statistics for the second series Bulgaria are highly significant for all regressions except the pre-crisis one with the EMU index. Similarly, the Q-stats for the second series of regressions involving Romania are significant pre-crisis. This points to large scale autocorrelation in the residuals, which may be due to an inadequate model order or the need for additional differencing (Caporale et al. 2006 p. 382).

The results for the first, second and fourth hypothesis, set earlier in the paper, can easily be deducted from table 6. The first null hypothesis of no cointegration pre-crisis is rejected for the Czech Republic and Hungary in the case of Greece, and for Hungary in the case of the EMU index.

The second null hypothesis of no crisis time cointegration with Greece is rejected for Hungary and Romania. The same hypothesis with the EMU index is rejected for all except Hungary.

The study fails to reject the fourth hypothesis of symmetric spillovers in all cases for Greece, but then rejects it in every case of eurozone spillovers.

The third hypothesis is examined with the aid of an asymptotic t-test. For the first part of the null hypothesis:

$$t = \frac{a_{12(crisis)} - a_{12(pre-\ crisis)}}{se\ (a_{12(crisis)} + a_{12(pre-\ crisis)})} \sim t_{(N-K)} \tag{21}$$

and for the second part of the hypothesis:

$$t = \frac{g_{12(crisis)} - g_{12(pre-\ crisis)}}{se\ (g_{12(crisis)} + g_{12(pre-\ crisis)})} \sim t_{(N-K)} \tag{22}$$

where the spillover coefficients are divided by their standard errors to acquire a value for the t-statistic. The significance of the t-statistics is then measured from a t-distribution where the degrees of freedom are given by the number of observations, $N$ and the number of parameters estimated, $K$. (Hill et al. 2012 p. 597)

Since the null hypothesis tests whether contagion is present through a positive increase in crisis spillovers, the null hypothesis will not be rejected if the t-statistic is significant but negative.

Despite this the distribution used is still two-tailed, with the critical values for $-t_c < 0 < t_c$ being around -1.962 and 1.962, respectively.

The required spillover coefficients and standard errors can be found in appendix 2. For now the results of the t-tests are presented in table 7. For values exceeding 1.962 the null hypothesis is rejected.

| | Czech | Hungary | Bulgaria | Romania | | Czech | Hungary | Bulgaria | Romania |
|---|---|---|---|---|---|---|---|---|---|
| $sho.t_g$ | *2,1284** | 1,5114 | 0,8791 | -0,7853 | $sho.t_{EMU}$ | 1,5243 | 1,3077 | *2,4768** | 0,9567 |
| $vol.t_g$ | -0,8295 | 0,5353 | -0,9546 | *2,0682** | $vol.t_{EMU}$ | -0,4403 | -0,5153 | 1,1120 | -2,4899 |

*Table 7. Contagion t-stats and their significance*

Symptoms of contagion are evident in shocks spillovers from Greece to the Czech Republic and from the EMU index to Bulgaria, as well as in volatility spillovers from Greece to Romania. All other spillovers can be seen as simply the effects of cointegration.

## 6. Conclusions

The indications are that diversifying one's portfolio with assets from former Eastern Bloc countries is still a tempting proposition. For the majority of the first decade of the 21st century, Hungary and the Czech Republic seem to have been as detached from eurozone markets as previous research had suggested. Even a small local market such as Greece had a larger effect than regional spillovers before the crisis began. This leads to the conclusion that the first four years of EU membership have not led to large scale cointegration for Czech and Hungarian markets.

As the EU membership of Romania and Bulgaria only slightly predates the commencement of the financial crisis, not much can be read into what effects joining the EU has had on their markets. Although return spillovers from Greece and the EMU index did partly dictate the direction Romanian and Bulgarian markets took, market fluctuations were in no way determined by Greek or EMU innovations.

During the crises the regional market became more prominent in leading returns than the local market. All countries except Hungary experienced the effects of the crisis on returns through the eurozone, while conversely the source of the crisis, Greece, did not have much of an impact in spreading it. This notion is enforced by the significant positive asymmetric response to EMU shock spillovers, as opposed to the indifference to Greek shocks, during the crisis.

Given that by and large the volatility of the countries studied is not affected by what happens in local or regional markets next to them, analysing the cause of what few spillovers do happen seems inconsequential. However it should be noted that of the few shock and volatility spillovers that are significant during this troubled period, two are due to contagion and three are down to cointegration. Contagion through volatility spillovers seems limited.

While this research has attempted to conclude how market liberalisation and the integration of former soviet states has progressed, it has not taken into account the remaining restrictions relating to capital, foreign investment, minimum period of investment etc. that are possibly still in place. Investigating how these restrictions affect the significance of spillovers in relation to this paper would be an interesting addition to research in the field and is likely to give new context to results such as those represented in this study.

## 7. References


Baele, L., (2004) "Volatility Spillover Effects in European Equity Markets", Journal of Financial and Quantitative Analysis, Volume 40, Issue no. 2, pages 373-401.

Baur, D (2003) "Testing for Contagion – Mean and Volatility Contagion", Journal of Multinational Financial Management, Volume 13, Issues no. 4-5, pages 405-422.

Bauwens, L, Laurent, S, Rombouts, J., (2006) "Multivariate GARCH Models: A Survey", Journal of Applied Econometrics, Volume 21, Issue no. 1, pages 79-109.

Bekaert, G and Harvey, C., (1997) "Emerging Market Volatility", Journal of Financial Economics, Volume 40, Issue no. 1, pages 29-77.

Bekaert, G, Harvey, C, Ng, A., (2005) "Market Integration and Contagion", The Journal of Business, Volume 78, Issue no. 1, pages 39-69.

Bollerslev, T., (1986) "Generalized Autoregressive Conditional Heteroskedasticity", Journal of Econometrics, Volume 31, Issue no. 3, pages 307-327.

Brooks, C., (2008) "Introductory Econometrics for Finance", 2nd edition, Cambridge University Press, Cambridge, UK

Caporale, G, Pittis, N, Spagnolo, N., (2006) "Volatility Transmission and Financial Crisis", Journal of Economics and Finance, Volume 30, Issue no. 3, pages 376-390.

Corsetti, G, Pericoli, M, Sbracia, M., (2005) "'Some Contagion, Some Interdependence': More Pitfalls in Tests of Financial Contagion", Journal of International Money and Finance, Volume 24, Issue no. 8, pages 1177-1199.

Dimitriou, D, Mpitsos, P, Simos, T., (2011) "Dynamic Linkages and Interdependence between Mediterranean Region EMU Markets during 2007 Financial Crisis", International Research Journal of Finance and Economics, Issue no. 71, pages 70-76.

Engle, R., (1982) "Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation", Econometrica, Volume 50, Issue no. 4, pages 987-1007.

Engle, R and Kroner, K., (1995) “Multivariate Simultaneous Generalized ARCH”, Econometric Theory, Volume 11, Issue no. 1, pages 122-150.

Estima (2004) “Rats 6 User Guide”, Estima, USA

Forbes, K and Rigobon, R (2002) “No Contagion, Only Interdependence: Measuring Stock Market Comovements”, Journal of Finance, Volume 57, issue no. 5, pages 2223-2261.

French, K and Porteba, J., (1991) “Investor Diversification and International Equity Markets”, The American Economic Review, Volume 81, Issue no. 2, pages 222-226.

Grubel, H., (1968) “Internationally Diversified Portfolios: Welfare Gains and Capital Flows”, American Economic Review, Volume 58, pages 1299-1314.

Hill, R, Griffiths, W, Lim, G (2012) “Principles of Econometrics”, 4th edition, John Wiley & Sons (Asia) Pte Ltd., Asia

Hull, J., (2000) “Options, Futures, and Other Derivatives”, 4th edition, Prentice Hall, Upper Saddle River, USA

Karanasos, M and Kim, J., (2005) “The Inflation-Output Variability Relationship in the G3: A Bivariate GARCH (BEKK) Approach”, Risk Letters, Volume 1, Issue no. 2, pages 17-22.

Kim, J, Moshirian, F, Wu, E., (2005) ”Dynamic Stock Market Integration Driven by the European Monetary Union: An Empirical Analysis”, Journal of Banking & Finance, Volume 29, issue no. 10, pages 2475-2502

Kasch- Haroutounian, M and Price, S., (2001) “Volatility in the Transition Markets of Central Europe”, Applied Financial Economics, Volume 11, issue no. 1, pages 93-105

Kroner, K and Ng, V., (1998) “Modelling Asymmetric Comovements on Asset Returns”, The Review of Financial Studies, Volume 11, Issue no. 4, pages 817-844.

Li, H and Majerowska, E., (2008) “Testing Stock Market Linkages for Poland and Hungary: A Multivariate GARCH Approach”, Research in International Business and Finance, Volume 22, Issue no. 3, pages 247-266.

Markowitz, H., (1959) “Portfolio Selection: Efficient Diversification of Investments”, Blackwell, New York, USA.

Ng, A., (2000) “Volatility Spillover effects from Japan and the US to the Pacific–Basin”, Journal of International Money and Finance, Volume 19, Issue no. 2, pages 207–233.

Panayiotis, A and Vasila, A., (2010) “Equity Interconnections in Major European Markets”, European Research Studies, Volume 8, Issue no. 3 pages 109-132.

Pedrescu, O and Stancu, S., (2011) “Portfolio Risk Analysis using ARCH and GARCH Models in the Context of the Global Financial Crisis”, Theoretical and Applied Economics, Volume 18, Issue no. 2, pages 75-88.

Rockinger, M and Urga, G., (2001) “A Time-Varying Parameter Model to Test for Predictability and Integration in the Stock Markets of Transition Economies”, Journal of Business and Economic Statistics, Volume 19, Issue no. 1, pages 73-84.

Scheicher, M., (2001) “The Comovements of Stock Markets in Hungary, Poland and Czech Republic”, International Journal of Finance and Economics, Volume 6, Issue no. 1, pages 27-39.

Simon, C and Blume, L., (1994) “Mathematics for Economists”, W. W. Norton & Company, Inc., New York, USA.

Tai, C., (2007) “Market Integration and Contagion: Evidence from Asian Emerging Stock and Foreign Exchange Markets”, Emerging Markets Review, Volume 8, Issue no. 4, pages 264-283.

Tobin, J., (1958) "Liquidity Preference as Behavior Towards Risk", Review of Economic Studies, Volume 25, Issue no. 1, pages 65-86.

## 7.1 Other References

Bloomberg website reference 1 “Greek Debt Deal Sees 50% Haircut in Notional Debt, Official Says” [available at: http://www.bloomberg.com/news/2011-10-27/greek-debt-deal-sees-50-haircut-in-notional-debt-official-says.html ] [created: 27.10.2011] [retrieved: 23.11.2011]

ECB website reference 1 “Long-term interest rate statistics for EU Member States” [available at: http://www.ecb.int/stats/money/long/html/index.en.html ] [updated 11.11.2011] [retrieved: 23.11.2011]

The Economist website reference 1 “The PIIGS that won't fly” [available at: http://www.economist.com/node/15838029 ][created: 18.5.2010] [retrieved: 23.11.2011]

European Union website reference 1 “Basic information on the European Union” [available at: http://europa.eu/about-eu/basic-information/index_en.htm ] [retrieved: 22.11.2011]

European Union website reference 2 “The Euro” [available at: http://ec.europa.eu/economy_finance/euro/index_en.htm ] [retrieved: 22.11.2011]

Reuters website reference 1 “UPDATE 2-Greek party leader offers bailout pledge, doubts remain” [available at: http://www.reuters.com/article/2011/11/23/greece-idUSL5E7MN35K20111123 ] [created: 23.11.2011][retrieved: 23.11.2011]

# 8. Appendices

Appendix 1.

Test for Equality of Means Between Series
Date: 02/27/12 Time: 19:45
Sample: 12/03/2007 11/11/2011
Included observations: 1030

| Method | df | Value | Probability |
|---|---|---|---|
| t-test | 2058 | -0.039983 | 0.9681 |
| Satterthwaite-Welch t-test* | 1974.784 | -0.039983 | 0.9681 |
| Anova F-test | (1, 2058) | 0.001599 | 0.9681 |
| Welch F-test* | (1, 1974.78) | 0.001599 | 0.9681 |

*Test allows for unequal cell variances

Analysis of Variance

| Source of Variation | df | Sum of Sq. | Mean Sq. |
|---|---|---|---|
| Between | 1 | 5.43E-07 | 5.43E-07 |
| Within | 2058 | 0.699218 | 0.000340 |
| Total | 2059 | 0.699218 | 0.000340 |

T-test of means between Bulgaria MSCI data and Bulgaria stock exchange data

Test for Equality of Means Between Series
Date: 02/27/12 Time: 19:51
Sample: 12/03/2007 11/11/2011
Included observations: 1030

| Method | df | Value | Probability |
|---|---|---|---|
| t-test | 2058 | -0.243930 | 0.8073 |
| Satterthwaite-Welch t-test* | 2020.896 | -0.243930 | 0.8073 |
| Anova F-test | (1, 2058) | 0.059502 | 0.8073 |
| Welch F-test* | (1, 2020.9) | 0.059502 | 0.8073 |

*Test allows for unequal cell variances

Analysis of Variance

| Source of Variation | df | Sum of Sq. | Mean Sq. |
|---|---|---|---|
| Between | 1 | 3.29E-05 | 3.29E-05 |
| Within | 2058 | 1.136895 | 0.000552 |
| Total | 2059 | 1.136927 | 0.000552 |

T-test of means between Romania MSCI data and Romania stock exchange data

Appendix 2.

| | Variable | Coeff | Std Error | T-Stat | Signif |
|---|---|---|---|---|---|
| 1 | GREECE{1} | 0,0675 | 0,0221 | 3,0602 | 0,0022 |
| 2 | CZECH{1} | 0,0393 | 0,0166 | 2,3713 | 0,0177 |
| 3 | Constant | 0,0003 | 0,0002 | 1,4893 | 0,1364 |
| 4 | GREECE{1} | -0,0134 | 0,0237 | -0,5663 | 0,5712 |
| 5 | CZECH{1} | 0,0553 | 0,0241 | 2,2919 | 0,0219 |
| 6 | Constant | 0,0012 | 0,0003 | 4,4228 | 0,0000 |
| 7 | C(1,1) | 0,0020 | 0,0003 | 7,5296 | 0,0000 |
| 8 | C(2,1) | 0,0028 | 0,0006 | 4,7452 | 0,0000 |
| 9 | C(2,2) | 0,0034 | 0,0006 | 6,0764 | 0,0000 |
| 10 | A(1,1) | 0,1473 | 0,0313 | 4,7090 | 0,0000 |
| 11 | A(1,2) | -0,0852 | 0,0323 | -2,6409 | 0,0083 |
| 12 | A(2,1) | -0,0133 | 0,0251 | -0,5315 | 0,5951 |
| 13 | A(2,2) | 0,1003 | 0,0421 | 2,3858 | 0,0170 |
| 14 | B(1,1) | 0,9635 | 0,0087 | 110,7814 | 0,0000 |
| 15 | B(1,2) | 0,0152 | 0,0138 | 1,1013 | 0,2708 |
| 16 | B(2,1) | -0,0334 | 0,0116 | -2,8866 | 0,0039 |
| 17 | B(2,2) | 0,8865 | 0,0170 | 52,0546 | 0,0000 |
| 18 | D(1,1) | 0,2731 | 0,0300 | 9,0883 | 0,0000 |
| 19 | D(1,2) | 0,0185 | 0,0466 | 0,3976 | 0,6909 |
| 20 | D(2,1) | 0,0567 | 0,0254 | 2,2339 | 0,0255 |
| 21 | D(2,2) | 0,4151 | 0,0428 | 9,7050 | 0,0000 |
| | Q*12 (series 1) | 11,6137 | | | 0,4772 |
| | Q*24 (series 1) | 28,4099 | | | 0,2431 |
| | Q*12 (series 2) | 13,4827 | | | 0,3350 |
| | Q*24 (series 2) | 30,0898 | | | 0,1818 |
| | Log likelihood | 10567,57 | | | |

VAR-GARCH-BEKK results. Variables: (1) Greece, (2) Czech Republic, Pre-crisis

| | Variable | Coeff | Std Error | T-Stat | Signif |
|---|---|---|---|---|---|
| 1 | GREECE{1} | 0,0735 | 0,0232 | 3,1634 | 0,0016 |
| 2 | HUNGARY{1} | 0,0049 | 0,0158 | 0,3131 | 0,7542 |
| 3 | Constant | 0,0005 | 0,0003 | 1,9551 | 0,0506 |
| 4 | GREECE{1} | -0,0080 | 0,0282 | -0,2839 | 0,7765 |
| 5 | HUNGARY{1} | 0,0256 | 0,0243 | 1,0553 | 0,2913 |
| 6 | Constant | 0,0008 | 0,0003 | 2,3972 | 0,0165 |
| 7 | C(1,1) | 0,0020 | 0,0003 | 5,8709 | 0,0000 |
| 8 | C(2,1) | 0,0017 | 0,0010 | 1,6436 | 0,1003 |
| 9 | C(2,2) | 0,0042 | 0,0006 | 7,3651 | 0,0000 |
| 10 | A(1,1) | 0,1555 | 0,0313 | 4,9683 | 0,0000 |
| 11 | A(1,2) | -0,1254 | 0,0392 | -3,2013 | 0,0014 |
| 12 | A(2,1) | 0,0583 | 0,0213 | 2,7368 | 0,0062 |
| 13 | A(2,2) | 0,1683 | 0,0388 | 4,3333 | 0,0000 |
| 14 | B(1,1) | 0,9573 | 0,0119 | 80,2289 | 0,0000 |
| 15 | B(1,2) | 0,0397 | 0,0172 | 2,3032 | 0,0213 |

| | | | | | |
|---|---|---|---|---|---|
| 16 | B(2,1) | -0,0273 | 0,0131 | -2,0868 | 0,0369 |
| 17 | B(2,2) | 0,9053 | 0,0199 | 45,5330 | 0,0000 |
| 18 | D(1,1) | -0,2887 | 0,0364 | -7,9392 | 0,0000 |
| 19 | D(1,2) | -0,0675 | 0,0487 | -1,3855 | 0,1659 |
| 20 | D(2,1) | -0,0049 | 0,0349 | -0,1395 | 0,8890 |
| 21 | D(2,2) | -0,2865 | 0,0423 | -6,7754 | 0,0000 |
| | Q*12 (series 1) | 11,3720 | | | 0,4973 |
| | Q*24 (series 1) | 28,3178 | | | 0,2469 |
| | Q*12 (series 2) | 13,1892 | | | 0,3554 |
| | Q*24 (series 2) | 23,3246 | | | 0,5007 |
| | Log likelihood | 10281,27 | | | |

VAR-GARCH-BEKK results. Variables: (1) Greece, (2) Hungary, Pre-crisis

| | Variable | Coeff | Std Error | T-Stat | Signif |
|---|---|---|---|---|---|
| 1 | GREECE{1} | 0,0760 | 0,0231 | 3,2937 | 0,0010 |
| 2 | BULGARIA{1} | 0,0091 | 0,0192 | 0,4746 | 0,6351 |
| 3 | Constant | 0,0004 | 0,0003 | 1,5404 | 0,1235 |
| 4 | GREECE{1} | 0,0366 | 0,0163 | 2,2500 | 0,0244 |
| 5 | BULGARIA{1} | 0,1423 | 0,0278 | 5,1174 | 0,0000 |
| 6 | Constant | 0,0009 | 0,0002 | 4,6393 | 0,0000 |
| 7 | C(1,1) | 0,0023 | 0,0003 | 8,2138 | 0,0000 |
| 8 | C(2,1) | -0,0002 | 0,0003 | -0,6534 | 0,5135 |
| 9 | C(2,2) | 0,0013 | 0,0003 | 4,5956 | 0,0000 |
| 10 | A(1,1) | 0,1213 | 0,0308 | 3,9422 | 0,0001 |
| 11 | A(1,2) | -0,0157 | 0,0190 | -0,8295 | 0,4068 |
| 12 | A(2,1) | 0,0222 | 0,0228 | 0,9736 | 0,3302 |
| 13 | A(2,2) | 0,3619 | 0,0360 | 10,0601 | 0,0000 |
| 14 | B(1,1) | 0,9462 | 0,0085 | 110,9650 | 0,0000 |
| 15 | B(1,2) | 0,0071 | 0,0078 | 0,9128 | 0,3614 |
| 16 | B(2,1) | -0,0014 | 0,0090 | -0,1547 | 0,8771 |
| 17 | B(2,2) | 0,9342 | 0,0127 | 73,3312 | 0,0000 |
| 18 | D(1,1) | 0,3158 | 0,0330 | 9,5774 | 0,0000 |
| 19 | D(1,2) | -0,0138 | 0,0264 | -0,5223 | 0,6014 |
| 20 | D(2,1) | 0,0269 | 0,0343 | 0,7847 | 0,4326 |
| 21 | D(2,2) | -0,0051 | 0,0730 | -0,0705 | 0,9438 |
| | Q*12 (series 1) | 12,0508 | | | 0,4416 |
| | Q*24 (series 1) | 29,2888 | | | 0,2095 |
| | Q*12 (series 2) | 22,2061 | | | 0,0353 |
| | Q*24 (series 2) | 29,6418 | | | 0,1969 |
| | Log likelihood | 10750,94 | | | |

VAR-GARCH-BEKK results. Variables: (1) Greece, (2) Bulgaria, Pre-crisis

| | Variable | Coeff | Std Error | T-Stat | Signif |
|---|---|---|---|---|---|
| 1 | GREECE{1} | 0,0673 | 0,0246 | 2,7378 | 0,0062 |
| 2 | ROMANIA{1} | -0,0039 | 0,0169 | -0,2304 | 0,8178 |
| 3 | Constant | 0,0005 | 0,0003 | 2,0791 | 0,0376 |
| 4 | GREECE{1} | 0,0614 | 0,0229 | 2,6768 | 0,0074 |
| 5 | ROMANIA{1} | 0,1226 | 0,0262 | 4,6768 | 0,0000 |
| 6 | Constant | 0,0011 | 0,0003 | 3,8446 | 0,0001 |
| 7 | C(1,1) | 0,0025 | 0,0003 | 8,4893 | 0,0000 |

| | | | | | |
|---|---|---|---|---|---|
| 8 | C(2,1) | 0,0003 | 0,0004 | 0,6860 | 0,4927 |
| 9 | C(2,2) | 0,0019 | 0,0004 | 4,4817 | 0,0000 |
| 10 | A(1,1) | 0,1598 | 0,0273 | 5,8464 | 0,0000 |
| 11 | A(1,2) | 0,0251 | 0,0250 | 1,0060 | 0,3144 |
| 12 | A(2,1) | -0,0048 | 0,0198 | -0,2415 | 0,8092 |
| 13 | A(2,2) | 0,2968 | 0,0304 | 9,7689 | 0,0000 |
| 14 | B(1,1) | 0,9366 | 0,0103 | 91,2759 | 0,0000 |
| 15 | B(1,2) | -0,0135 | 0,0113 | -1,1917 | 0,2334 |
| 16 | B(2,1) | 0,0010 | 0,0073 | 0,1358 | 0,8920 |
| 17 | B(2,2) | 0,9454 | 0,0123 | 76,8593 | 0,0000 |
| 18 | D(1,1) | 0,3044 | 0,0315 | 9,6707 | 0,0000 |
| 19 | D(1,2) | 0,0774 | 0,0469 | 1,6515 | 0,0986 |
| 20 | D(2,1) | 0,0437 | 0,0265 | 1,6470 | 0,0996 |
| 21 | D(2,2) | 0,0718 | 0,0626 | 1,1470 | 0,2514 |
| | Q*12 (series 1) | 12,2504 | | | 0,4258 |
| | Q*24 (series 1) | 29,3866 | | | 0,2059 |
| | Q*12 (series 2) | 23,6712 | | | 0,0225 |
| | Q*24 (series 2) | 40,5075 | | | 0,0189 |
| | Log likelihood | 10449,12 | | | |

VAR-GARCH-BEKK results. Variables: (1) Greece, (2) Romania, Pre-crisis

| | Variable | Coeff | Std Error | T-Stat | Signif |
|---|---|---|---|---|---|
| 1 | EMU{1} | -0,0614 | 0,0211 | -2,9147 | 0,0036 |
| 2 | CZECH{1} | -0,0050 | 0,0151 | -0,3336 | 0,7387 |
| 3 | Constant | 0,0004 | 0,0002 | 2,3886 | 0,0169 |
| 4 | EMU{1} | -0,0318 | 0,0242 | -1,3149 | 0,1886 |
| 5 | CZECH{1} | 0,0410 | 0,0246 | 1,6664 | 0,0956 |
| 6 | Constant | 0,0013 | 0,0003 | 4,5633 | 0,0000 |
| 7 | C(1,1) | 0,0013 | 0,0001 | 12,1289 | 0,0000 |
| 8 | C(2,1) | 0,0022 | 0,0005 | 4,4152 | 0,0000 |
| 9 | C(2,2) | 0,0035 | 0,0003 | 12,6198 | 0,0000 |
| 10 | A(1,1) | -0,0331 | 0,0309 | -1,0711 | 0,2841 |
| 11 | A(1,2) | -0,0016 | 0,0498 | -0,0328 | 0,9738 |
| 12 | A(2,1) | 0,0042 | 0,0199 | 0,2126 | 0,8316 |
| 13 | A(2,2) | 0,1872 | 0,0417 | 4,4892 | 0,0000 |
| 14 | B(1,1) | 0,9625 | 0,0048 | 199,8511 | 0,0000 |
| 15 | B(1,2) | 0,0093 | 0,0099 | 0,9424 | 0,3460 |
| 16 | B(2,1) | -0,0101 | 0,0070 | -1,4344 | 0,1515 |
| 17 | B(2,2) | 0,8922 | 0,0164 | 54,2488 | 0,0000 |
| 18 | D(1,1) | -0,3465 | 0,0246 | -14,0750 | 0,0000 |
| 19 | D(1,2) | -0,0096 | 0,0439 | -0,2199 | 0,8260 |
| 20 | D(2,1) | -0,0223 | 0,0193 | -1,1538 | 0,2486 |
| 21 | D(2,2) | -0,3748 | 0,0495 | -7,5767 | 0,0000 |
| | Q*12 (series 1) | 16,6239 | | | 0,1643 |
| | Q*24 (series 1) | 22,0768 | | | 0,5747 |
| | Q*12 (series 2) | 14,3782 | | | 0,2772 |
| | Q*24 (series 2) | 30,2464 | | | 0,1969 |
| | Log likelihood | 10780,67 | | | |

VAR-GARCH-BEKK results. Variables: (1) EMU Index, (2) Czech Republic, Pre-crisis

| | Variable | Coeff | Std Error | T-Stat | Signif |
|---|---|---|---|---|---|
| 1 | EMU{1} | -0,0524 | 0,0228 | -2,2998 | 0,0215 |
| 2 | HUNGARY{1} | -0,0248 | 0,0121 | -2,0486 | 0,0405 |
| 3 | Constant | 0,0004 | 0,0002 | 2,5527 | 0,0107 |
| 4 | EMU{1} | -0,0021 | 0,0299 | -0,0695 | 0,9446 |
| 5 | HUNGARY{1} | 0,0243 | 0,0254 | 0,9565 | 0,3388 |
| 6 | Constant | 0,0008 | 0,0003 | 2,4673 | 0,0136 |
| 7 | C(1,1) | -0,0014 | 0,0001 | -10,7024 | 0,0000 |
| 8 | C(2,1) | -0,0019 | 0,0008 | -2,5611 | 0,0104 |
| 9 | C(2,2) | -0,0035 | 0,0004 | -8,4897 | 0,0000 |
| 10 | A(1,1) | 0,0892 | 0,0272 | 3,2747 | 0,0011 |
| 11 | A(1,2) | -0,1150 | 0,0299 | -3,8522 | 0,0001 |
| 12 | A(2,1) | -0,0012 | 0,0106 | -0,1129 | 0,9101 |
| 13 | A(2,2) | 0,2240 | 0,0301 | 7,4461 | 0,0000 |
| 14 | B(1,1) | 0,9549 | 0,0072 | 131,9828 | 0,0000 |
| 15 | B(1,2) | 0,0112 | 0,0102 | 1,0905 | 0,2755 |
| 16 | B(2,1) | -0,0059 | 0,0069 | -0,8554 | 0,3923 |
| 17 | B(2,2) | 0,9198 | 0,0137 | 67,1546 | 0,0000 |
| 18 | D(1,1) | 0,3693 | 0,0305 | 12,0999 | 0,0000 |
| 19 | D(1,2) | 0,0680 | 0,0475 | 1,4294 | 0,1529 |
| 20 | D(2,1) | -0,0059 | 0,0207 | -0,2836 | 0,7767 |
| 21 | D(2,2) | 0,2621 | 0,0397 | 6,6042 | 0,0000 |
| | Q*12 (series 1) | 16,6269 | | | 0,1642 |
| | Q*24 (series 1) | 22,2167 | | | 0,5663 |
| | Q*12 (series 2) | 13,6159 | | | 0,3259 |
| | Q*24 (series 2) | 23,9799 | | | 0,4627 |
| | Log likelihood | 10563,36 | | | |

VAR-GARCH-BEKK results. Variables: (1) EMU Index, (2) Hungary, Pre-crisis

| | Variable | Coeff | Std Error | T-Stat | Signif |
|---|---|---|---|---|---|
| 1 | EMU{1} | -0,0590 | 0,0240 | -2,4535 | 0,0141 |
| 2 | BULGARIA{1} | -0,0191 | 0,0167 | -1,1420 | 0,2535 |
| 3 | Constant | 0,0004 | 0,0002 | 1,8737 | 0,0610 |
| 4 | EMU{1} | 0,0300 | 0,0197 | 1,5267 | 0,1268 |
| 5 | BULGARIA{1} | 0,1700 | 0,0242 | 7,0304 | 0,0000 |
| 6 | Constant | 0,0008 | 0,0002 | 3,7110 | 0,0002 |
| 7 | C(1,1) | 0,0013 | 0,0001 | 9,2431 | 0,0000 |
| 8 | C(2,1) | 0,0002 | 0,0003 | 0,6090 | 0,5425 |
| 9 | C(2,2) | -0,0020 | 0,0003 | -6,3811 | 0,0000 |
| 10 | A(1,1) | 0,0275 | 0,0308 | 0,8923 | 0,3722 |
| 11 | A(1,2) | -0,0654 | 0,0393 | -1,6628 | 0,0964 |
| 12 | A(2,1) | 0,0157 | 0,0227 | 0,6897 | 0,4904 |
| 13 | A(2,2) | 0,4781 | 0,0406 | 11,7694 | 0,0000 |
| 14 | B(1,1) | 0,9522 | 0,0055 | 174,0861 | 0,0000 |
| 15 | B(1,2) | -0,0241 | 0,0135 | -1,7803 | 0,0750 |
| 16 | B(2,1) | -0,0053 | 0,0108 | -0,4861 | 0,6269 |
| 17 | B(2,2) | 0,8778 | 0,0204 | 43,0086 | 0,0000 |
| 18 | D(1,1) | 0,3754 | 0,0255 | 14,7168 | 0,0000 |
| 19 | D(1,2) | 0,1306 | 0,0565 | 2,3131 | 0,0207 |
| 20 | D(2,1) | 0,0412 | 0,0198 | 2,0861 | 0,0370 |

| | | | | | |
|---|---|---|---|---|---|
| 21 | D(2,2) | 0,0622 | 0,0615 | 1,0107 | 0,3121 |
| | Q*12 (series 1) | 16,6400 | | | 0,1636 |
| | Q*24 (series 1) | 22,1626 | | | 0,5696 |
| | Q*12 (series 2) | 20,0178 | | | 0,0668 |
| | Q*24 (series 2) | 28,6805 | | | 0,2324 |
| | Log likelihood | 10955,50 | | | |

VAR-GARCH-BEKK results. Variables: (1) EMU Index, (2) Bulgaria, Pre-crisis

| | Variable | Coeff | Std Error | T-Stat | Signif |
|---|---|---|---|---|---|
| 1 | EMU{1} | -0,0710 | 0,0242 | -2,9347 | 0,0033 |
| 2 | ROMANIA{1} | 0,0056 | 0,0135 | 0,4139 | 0,6790 |
| 3 | Constant | 0,0004 | 0,0002 | 1,9987 | 0,0456 |
| 4 | EMU{1} | 0,0450 | 0,0218 | 2,0650 | 0,0389 |
| 5 | ROMANIA{1} | 0,1333 | 0,0236 | 5,6397 | 0,0000 |
| 6 | Constant | 0,0010 | 0,0003 | 3,5058 | 0,0005 |
| 7 | C(1,1) | 0,0013 | 0,0001 | 9,6463 | 0,0000 |
| 8 | C(2,1) | 0,0000 | 0,0003 | 0,1209 | 0,9037 |
| 9 | C(2,2) | 0,0019 | 0,0004 | 5,3333 | 0,0000 |
| 10 | A(1,1) | 0,0475 | 0,0238 | 1,9935 | 0,0462 |
| 11 | A(1,2) | -0,0379 | 0,0227 | -1,6670 | 0,0955 |
| 12 | A(2,1) | 0,0012 | 0,0105 | 0,1140 | 0,9093 |
| 13 | A(2,2) | 0,3063 | 0,0273 | 11,2329 | 0,0000 |
| 14 | B(1,1) | 0,9531 | 0,0056 | 169,6681 | 0,0000 |
| 15 | B(1,2) | -0,0081 | 0,0070 | -1,1476 | 0,2511 |
| 16 | B(2,1) | 0,0009 | 0,0038 | 0,2243 | 0,8226 |
| 17 | B(2,2) | 0,9388 | 0,0120 | 78,3379 | 0,0000 |
| 18 | D(1,1) | -0,3820 | 0,0263 | -14,5463 | 0,0000 |
| 19 | D(1,2) | -0,0628 | 0,0345 | -1,8209 | 0,0686 |
| 20 | D(2,1) | 0,0140 | 0,0170 | 0,8232 | 0,4104 |
| 21 | D(2,2) | -0,1635 | 0,0507 | -3,2216 | 0,0013 |
| | Q*12 (series 1) | 17,1874 | | | 0,1427 |
| | Q*24 (series 1) | 22,5136 | | | 0,5486 |
| | Q*12 (series 2) | 23,9695 | | | 0,0205 |
| | Q*24 (series 2) | 41,1501 | | | 0,0160 |
| | Log likelihood | 10639,43 | | | |

VAR-GARCH-BEKK results. Variables: (1) EMU Index, (2) Romania, Pre-crisis

| | Variable | Coeff | Std Error | T-Stat | Signif |
|---|---|---|---|---|---|
| 1 | GREECE{1} | -0,0374 | 0,0341 | -1,0961 | 0,2730 |
| 2 | CZECH{1} | 0,0764 | 0,0503 | 1,5185 | 0,1289 |
| 3 | Constant | -0,0013 | 0,0008 | -1,5320 | 0,1255 |
| 4 | GREECE{1} | 0,0214 | 0,0168 | 1,2784 | 0,2011 |
| 5 | CZECH{1} | -0,0154 | 0,0344 | -0,4478 | 0,6543 |
| 6 | Constant | 0,0004 | 0,0004 | 0,8931 | 0,3718 |
| 7 | C(1,1) | 0,0073 | 0,0016 | 4,5096 | 0,0000 |
| 8 | C(2,1) | 0,0010 | 0,0010 | 0,9881 | 0,3231 |
| 9 | C(2,2) | 0,0017 | 0,0008 | 2,1662 | 0,0303 |
| 10 | A(1,1) | -0,0899 | 0,0637 | -1,4122 | 0,1579 |
| 11 | A(1,2) | 0,0336 | 0,0236 | 1,4264 | 0,1537 |
| 12 | A(2,1) | 0,1905 | 0,0628 | 3,0349 | 0,0024 |

| | | | | | |
|---|---|---|---|---|---|
| 13 | A(2,2) | 0,2644 | 0,0506 | 5,2223 | 0,0000 |
| 14 | B(1,1) | 0,9189 | 0,0306 | 30,0167 | 0,0000 |
| 15 | B(1,2) | -0,0127 | 0,0198 | -0,6397 | 0,5224 |
| 16 | B(2,1) | -0,0046 | 0,0236 | -0,1954 | 0,8451 |
| 17 | B(2,2) | 0,9307 | 0,0192 | 48,3910 | 0,0000 |
| 18 | D(1,1) | 0,3615 | 0,0570 | 6,3464 | 0,0000 |
| 19 | D(1,2) | 0,0543 | 0,0318 | 1,7091 | 0,0874 |
| 20 | D(2,1) | 0,0422 | 0,0743 | 0,5678 | 0,5701 |
| 21 | D(2,2) | 0,2769 | 0,0704 | 3,9363 | 0,0001 |
| | Q*12 (series 1) | 13,9948 | | | 0,3010 |
| | Q*24 (series 1) | 25,4714 | | | 0,3805 |
| | Q*12 (series 2) | 12,7242 | | | 0,3894 |
| | Q*24 (series 2) | 21,1228 | | | 0,6315 |
| | Log likelihood | 4189,74 | | | |

VAR-GARCH-BEKK results. Variables: (1) Greece, (2) Czech Republic, Crisis

| | Variable | Coeff | Std Error | T-Stat | Signif |
|---|---|---|---|---|---|
| 1 | GREECE{1} | -0,0544 | 0,0328 | -1,6563 | 0,0977 |
| 2 | HUNGARY{1} | 0,1307 | 0,0311 | 4,1995 | 0,0000 |
| 3 | Constant | -0,0014 | 0,0008 | -1,7603 | 0,0784 |
| 4 | GREECE{1} | 0,0069 | 0,0312 | 0,2217 | 0,8245 |
| 5 | HUNGARY{1} | 0,0294 | 0,0361 | 0,8156 | 0,4147 |
| 6 | Constant | 0,0003 | 0,0008 | 0,3729 | 0,7092 |
| 7 | C(1,1) | 0,0053 | 0,0011 | 4,7844 | 0,0000 |
| 8 | C(2,1) | -0,0023 | 0,0011 | -2,1728 | 0,0298 |
| 9 | C(2,2) | -0,0002 | 0,0072 | -0,0223 | 0,9822 |
| 10 | A(1,1) | 0,1706 | 0,0456 | 3,7429 | 0,0002 |
| 11 | A(1,2) | -0,0127 | 0,0354 | -0,3570 | 0,7211 |
| 12 | A(2,1) | -0,0313 | 0,0439 | -0,7121 | 0,4764 |
| 13 | A(2,2) | 0,2596 | 0,0453 | 5,7268 | 0,0000 |
| 14 | B(1,1) | 0,9430 | 0,0164 | 57,3496 | 0,0000 |
| 15 | B(1,2) | 0,0575 | 0,0159 | 3,6132 | 0,0003 |
| 16 | B(2,1) | -0,0009 | 0,0119 | -0,0748 | 0,9403 |
| 17 | B(2,2) | 0,9230 | 0,0148 | 62,2350 | 0,0000 |
| 18 | D(1,1) | -0,3526 | 0,0506 | -6,9719 | 0,0000 |
| 19 | D(1,2) | 0,0090 | 0,0484 | 0,1860 | 0,8524 |
| 20 | D(2,1) | 0,2916 | 0,0395 | 7,3776 | 0,0000 |
| 21 | D(2,2) | 0,2494 | 0,0637 | 3,9142 | 0,0001 |
| | Q*12 (series 1) | 13,4154 | | | 0,3396 |
| | Q*24 (series 1) | 24,0488 | | | 0,4588 |
| | Q*12 (series 2) | 14,5090 | | | 0,2694 |
| | Q*24 (series 2) | 25,7751 | | | 0,3647 |
| | Log likelihood | 3765,62 | | | |

VAR-GARCH-BEKK results. Variables: (1) Greece, (2) Hungary, Crisis

| | Variable | Coeff | Std Error | T-Stat | Signif |
|---|---|---|---|---|---|
| 1 | GREECE{1} | 0,0164 | 0,0319 | 0,5138 | 0,6074 |
| 2 | BULGARIA{1} | -0,1139 | 0,0557 | -2,0440 | 0,0410 |
| 3 | Constant | -0,0014 | 0,0008 | -1,7396 | 0,0819 |
| 4 | GREECE{1} | 0,0069 | 0,0099 | 0,6969 | 0,4859 |

| | | | | | |
|---|---|---|---|---|---|
| 5 | BULGARIA{1} | 0,0804 | 0,0380 | 2,1150 | 0,0344 |
| 6 | Constant | -0,0006 | 0,0003 | -2,1487 | 0,0317 |
| 7 | C(1,1) | 0,0070 | 0,0012 | 5,7054 | 0,0000 |
| 8 | C(2,1) | 0,0009 | 0,0006 | 1,4314 | 0,1523 |
| 9 | C(2,2) | 0,0019 | 0,0005 | 3,9935 | 0,0001 |
| 10 | A(1,1) | -0,0547 | 0,0418 | -1,3093 | 0,1904 |
| 11 | A(1,2) | 0,0117 | 0,0122 | 0,9561 | 0,3390 |
| 12 | A(2,1) | 0,1574 | 0,0559 | 2,8180 | 0,0048 |
| 13 | A(2,2) | 0,5011 | 0,0255 | 19,6583 | 0,0000 |
| 14 | B(1,1) | 0,9286 | 0,0203 | 45,6576 | 0,0000 |
| 15 | B(1,2) | -0,0096 | 0,0097 | -0,9882 | 0,3231 |
| 16 | B(2,1) | -0,0388 | 0,0245 | -1,5794 | 0,1143 |
| 17 | B(2,2) | 0,8443 | 0,0093 | 90,9381 | 0,0000 |
| 18 | D(1,1) | 0,3546 | 0,0410 | 8,6406 | 0,0000 |
| 19 | D(1,2) | -0,0031 | 0,0182 | -0,1692 | 0,8656 |
| 20 | D(2,1) | 0,1083 | 0,0769 | 1,4080 | 0,1591 |
| 21 | D(2,2) | 0,3452 | 0,0730 | 4,7269 | 0,0000 |
| | Q*12 (series 1) | 12,0303 | | | 0,4433 |
| | Q*24 (series 1) | 24,2160 | | | 0,4493 |
| | Q*12 (series 2) | 36,4111 | | | 0,0003 |
| | Q*24 (series 2) | 42,5847 | | | 0,0111 |
| | Log likelihood | 4358,93 | | | |

VAR-GARCH-BEKK results. Variables: (1) Greece, (2) Bulgaria, Crisis

| | Variable | Coeff | Std Error | T-Stat | Signif |
|---|---|---|---|---|---|
| 1 | GREECE{1} | -0,0222 | 0,0350 | -0,6348 | 0,5256 |
| 2 | ROMANIA{1} | 0,0426 | 0,0310 | 1,3729 | 0,1698 |
| 3 | Constant | -0,0014 | 0,0007 | -1,8956 | 0,0580 |
| 4 | GREECE{1} | 0,0114 | 0,0183 | 0,6199 | 0,5353 |
| 5 | ROMANIA{1} | 0,0629 | 0,0343 | 1,8317 | 0,0670 |
| 6 | Constant | 0,0004 | 0,0005 | 0,8604 | 0,3896 |
| 7 | C(1,1) | 0,0064 | 0,0011 | 5,5944 | 0,0000 |
| 8 | C(2,1) | -0,0023 | 0,0005 | -4,3923 | 0,0000 |
| 9 | C(2,2) | 0,0000 | 0,0012 | 0,0009 | 0,9993 |
| 10 | A(1,1) | 0,1202 | 0,0918 | 1,3096 | 0,1903 |
| 11 | A(1,2) | -0,0137 | 0,0244 | -0,5596 | 0,5758 |
| 12 | A(2,1) | 0,1029 | 0,0846 | 1,2165 | 0,2238 |
| 13 | A(2,2) | 0,4091 | 0,0484 | 8,4446 | 0,0000 |
| 14 | B(1,1) | 0,9239 | 0,0228 | 40,4436 | 0,0000 |
| 15 | B(1,2) | 0,0351 | 0,0122 | 2,8841 | 0,0039 |
| 16 | B(2,1) | 0,0120 | 0,0248 | 0,4827 | 0,6293 |
| 17 | B(2,2) | 0,8929 | 0,0177 | 50,3106 | 0,0000 |
| 18 | D(1,1) | 0,4125 | 0,0571 | 7,2180 | 0,0000 |
| 19 | D(1,2) | 0,0413 | 0,0369 | 1,1207 | 0,2624 |
| 20 | D(2,1) | -0,2508 | 0,1428 | -1,7560 | 0,0791 |
| 21 | D(2,2) | -0,1359 | 0,1560 | -0,8712 | 0,3837 |
| | Q*12 (series 1) | 12,7437 | | | 0,3879 |
| | Q*24 (series 1) | 23,4715 | | | 0,4921 |
| | Q*12 (series 2) | 9,7688 | | | 0,6362 |
| | Q*24 (series 2) | 26,5645 | | | 0,3252 |
| | Log likelihood | 4063,26 | | | |

VAR-GARCH-BEKK results. Variables: (1) Greece, (2) Romania, Crisis

| | Variable | Coeff | Std Error | T-Stat | Signif |
|---|---|---|---|---|---|
| 1 | EMU{1} | 0,0326 | 0,0386 | 0,8442 | 0,3986 |
| 2 | CZECH{1} | -0,0507 | 0,0337 | -1,5079 | 0,1316 |
| 3 | Constant | 0,0002 | 0,0004 | 0,5162 | 0,6057 |
| 4 | EMU{1} | 0,1192 | 0,0359 | 3,3230 | 0,0009 |
| 5 | CZECH{1} | -0,0772 | 0,0402 | -1,9216 | 0,0547 |
| 6 | Constant | 0,0004 | 0,0004 | 0,9713 | 0,3314 |
| 7 | C(1,1) | 0,0026 | 0,0008 | 3,2297 | 0,0012 |
| 8 | C(2,1) | -0,0010 | 0,0008 | -1,2863 | 0,1984 |
| 9 | C(2,2) | 0,0000 | 0,0018 | 0,0003 | 0,9997 |
| 10 | A(1,1) | 0,0316 | 0,0555 | 0,5686 | 0,5697 |
| 11 | A(1,2) | 0,1424 | 0,0447 | 3,1876 | 0,0014 |
| 12 | A(2,1) | 0,1095 | 0,0537 | 2,0394 | 0,0414 |
| 13 | A(2,2) | 0,2285 | 0,0397 | 5,7620 | 0,0000 |
| 14 | B(1,1) | 0,9091 | 0,0398 | 22,8450 | 0,0000 |
| 15 | B(1,2) | -0,0133 | 0,0415 | -0,3207 | 0,7484 |
| 16 | B(2,1) | 0,0360 | 0,0395 | 0,9093 | 0,3632 |
| 17 | B(2,2) | 0,9354 | 0,0319 | 29,3589 | 0,0000 |
| 18 | D(1,1) | 0,4954 | 0,0611 | 8,1029 | 0,0000 |
| 19 | D(1,2) | 0,3152 | 0,0608 | 5,1820 | 0,0000 |
| 20 | D(2,1) | -0,1256 | 0,0607 | -2,0697 | 0,0385 |
| 21 | D(2,2) | -0,2738 | 0,0816 | -3,3568 | 0,0008 |
| | Q*12 (series 1) | 8,7126 | | | 0,7273 |
| | Q*24 (series 1) | 16,8010 | | | 0,8570 |
| | Q*12 (series 2) | 12,0416 | | | 0,4423 |
| | Q*24 (series 2) | 21,1174 | | | 0,6318 |
| | Log likelihood | 4751,45 | | | |

VAR-GARCH-BEKK results. Variables: (1) EMU Index, (2) Czech Republic, Crisis

| | Variable | Coeff | Std Error | T-Stat | Signif |
|---|---|---|---|---|---|
| 1 | EMU{1} | -0,0037 | 0,0422 | -0,0869 | 0,9308 |
| 2 | HUNGARY{1} | 0,0141 | 0,0239 | 0,5892 | 0,5557 |
| 3 | Constant | -0,0003 | 0,0004 | -0,7244 | 0,4688 |
| 4 | EMU{1} | 0,0186 | 0,0706 | 0,2633 | 0,7923 |
| 5 | HUNGARY{1} | 0,0220 | 0,0438 | 0,5019 | 0,6158 |
| 6 | Constant | -0,0003 | 0,0007 | -0,3806 | 0,7035 |
| 7 | C(1,1) | 0,0020 | 0,0004 | 4,9641 | 0,0000 |
| 8 | C(2,1) | 0,0029 | 0,0007 | 3,9499 | 0,0001 |
| 9 | C(2,2) | 0,0014 | 0,0005 | 2,8243 | 0,0047 |
| 10 | A(1,1) | -0,0505 | 0,0801 | -0,6306 | 0,5283 |
| 11 | A(1,2) | 0,0726 | 0,1136 | 0,6393 | 0,5227 |
| 12 | A(2,1) | 0,0999 | 0,0461 | 2,1679 | 0,0302 |
| 13 | A(2,2) | 0,1847 | 0,0662 | 2,7901 | 0,0053 |
| 14 | B(1,1) | 0,9568 | 0,0165 | 58,0642 | 0,0000 |
| 15 | B(1,2) | -0,0104 | 0,0317 | -0,3295 | 0,7418 |
| 16 | B(2,1) | -0,0199 | 0,0090 | -2,2089 | 0,0272 |
| 17 | B(2,2) | 0,9488 | 0,0153 | 62,1327 | 0,0000 |
| 18 | D(1,1) | 0,4850 | 0,0789 | 6,1484 | 0,0000 |
| 19 | D(1,2) | 0,3551 | 0,1184 | 2,9980 | 0,0027 |
| 20 | D(2,1) | -0,0219 | 0,0535 | -0,4098 | 0,6820 |
| 21 | D(2,2) | 0,1294 | 0,0749 | 1,7275 | 0,0841 |
| | Q*12 (series 1) | 9,5166 | | | 0,6583 |

| | | | | | |
|---|---|---|---|---|---|
| | Q*24 (series 1) | 17,7144 | | | 0,8166 |
| | Q*12 (series 2) | 16,6020 | | | 0,1652 |
| | Q*24 (series 2) | 27,4384 | | | 0,2844 |
| | Log likelihood | 4420,50 | | | |

VAR-GARCH-BEKK results. Variables: (1) EMU Index, (2) Hungary, Crisis

| | Variable | Coeff | Std Error | T-Stat | Signif |
|---|---|---|---|---|---|
| 1 | EMU{1} | 0,0182 | 0,0336 | 0,5400 | 0,5892 |
| 2 | BULGARIA{1} | -0,0724 | 0,0299 | -2,4213 | 0,0155 |
| 3 | Constant | -0,0002 | 0,0004 | -0,4171 | 0,6766 |
| 4 | EMU{1} | 0,1097 | 0,0196 | 5,6071 | 0,0000 |
| 5 | BULGARIA{1} | 0,0284 | 0,0348 | 0,8141 | 0,4156 |
| 6 | Constant | -0,0005 | 0,0003 | -1,9659 | 0,0493 |
| 7 | C(1,1) | 0,0020 | 0,0003 | 6,9529 | 0,0000 |
| 8 | C(2,1) | 0,0001 | 0,0005 | 0,1030 | 0,9179 |
| 9 | C(2,2) | 0,0017 | 0,0003 | 6,9339 | 0,0000 |
| 10 | A(1,1) | -0,0012 | 0,0272 | -0,0457 | 0,9636 |
| 11 | A(1,2) | 0,0769 | 0,0181 | 4,2431 | 0,0000 |
| 12 | A(2,1) | 0,0472 | 0,0251 | 1,8839 | 0,0596 |
| 13 | A(2,2) | 0,4957 | 0,0247 | 20,0754 | 0,0000 |
| 14 | B(1,1) | 0,9421 | 0,0087 | 108,2473 | 0,0000 |
| 15 | B(1,2) | 0,0021 | 0,0100 | 0,2082 | 0,8351 |
| 16 | B(2,1) | 0,0139 | 0,0149 | 0,9352 | 0,3497 |
| 17 | B(2,2) | 0,8517 | 0,0095 | 89,9522 | 0,0000 |
| 18 | D(1,1) | 0,4274 | 0,0366 | 11,6831 | 0,0000 |
| 19 | D(1,2) | -0,0112 | 0,0319 | -0,3519 | 0,7249 |
| 20 | D(2,1) | 0,0197 | 0,0351 | 0,5598 | 0,5756 |
| 21 | D(2,2) | 0,1900 | 0,0662 | 2,8723 | 0,0041 |
| | Q*12 (series 1) | 7,3563 | | | 0,8332 |
| | Q*24 (series 1) | 16,3519 | | | 0,8750 |
| | Q*12 (series 2) | 40,0655 | | | 0,0001 |
| | Q*24 (series 2) | 46,4924 | | | 0,0039 |
| | Log likelihood | 4849,46 | | | |

VAR-GARCH-BEKK results. Variables: (1) EMU Index, (2) Bulgaria, Crisis

| | Variable | Coeff | Std Error | T-Stat | Signif |
|---|---|---|---|---|---|
| 1 | EMU{1} | -0,0002 | 0,0385 | -0,0065 | 0,9948 |
| 2 | ROMANIA{1} | 0,0024 | 0,0318 | 0,0754 | 0,9399 |
| 3 | Constant | 0,0001 | 0,0004 | 0,2270 | 0,8204 |
| 4 | EMU{1} | 0,1915 | 0,0404 | 4,7383 | 0,0000 |
| 5 | ROMANIA{1} | -0,0130 | 0,0385 | -0,3385 | 0,7350 |
| 6 | Constant | 0,0004 | 0,0005 | 0,9305 | 0,3521 |
| 7 | C(1,1) | 0,0021 | 0,0003 | 6,2612 | 0,0000 |
| 8 | C(2,1) | 0,0004 | 0,0005 | 0,7847 | 0,4326 |
| 9 | C(2,2) | 0,0000 | 0,0008 | 0,0000 | 1,0000 |
| 10 | A(1,1) | -0,0026 | 0,0487 | -0,0530 | 0,9577 |
| 11 | A(1,2) | 0,0285 | 0,0467 | 0,6113 | 0,5410 |
| 12 | A(2,1) | 0,1316 | 0,0506 | 2,6018 | 0,0093 |
| 13 | A(2,2) | 0,2765 | 0,0520 | 5,3187 | 0,0000 |
| 14 | B(1,1) | 0,9378 | 0,0096 | 97,2820 | 0,0000 |

| | | | | | |
|---|---|---|---|---|---|
| 15 | B(1,2) | -0,0537 | 0,0113 | -4,7514 | 0,0000 |
| 16 | B(2,1) | 0,0002 | 0,0094 | 0,0243 | 0,9806 |
| 17 | B(2,2) | 0,9680 | 0,0094 | 103,4945 | 0,0000 |
| 18 | D(1,1) | 0,3564 | 0,0522 | 6,8221 | 0,0000 |
| 19 | D(1,2) | 0,2601 | 0,0617 | 4,2189 | 0,0000 |
| 20 | D(2,1) | 0,0606 | 0,0476 | 1,2729 | 0,2031 |
| 21 | D(2,2) | 0,0319 | 0,0857 | 0,3720 | 0,7099 |
| | Q*12 (series 1) | 10,4039 | | | 0,5806 |
| | Q*24 (series 1) | 17,0862 | | | 0,8450 |
| | Q*12 (series 2) | 10,5357 | | | 0,5691 |
| | Q*24 (series 2) | 22,9356 | | | 0,5236 |
| | Log likelihood | 4575,72 | | | |

VAR-GARCH-BEKK results. Variables: (1) EMU Index, (2) Romania, Crisis