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EFFECTS OF GLOBAL INCIDENTS ON DYNAMIC CORRELATIONS OF EMERGING EUROPEAN COUNTRIES

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Abstract

This paper aims to investigate the international integration of stock markets of emerging European countries with the world market and to analyse the evolution of the integration levels in the case of four global/regional incidents; the 1998 Russian crisis, the 2001 Dotcom crisis and 9/11 shocks, the 2004 EU enlargement, and the 2007-2009 global financial crisis. The findings show that volatilities of the stock markets and correlation structures of those markets with the world market significantly change due to the impacts of global/regional incidents. Although, it is obvious that each incident has differential impact on each country depending on the internal dynamics of those countries at the times of incidents, the findings still clearly reveal the general common impacts of the investigated incidents on the return volatilities and the correlation structures of the sample countries with the world market.

Keywords: Dynamic Correlation, Stock Market Integration, Crisis, Emerging Europe

1. Introduction

Equity/stock market integration is the specific area of financial integration phenomenon which is subject to a considerable empirical investigation. Researches on international stock market integration carry crucial importance for international investors who seek for diversification opportunities to lower the risk and to increase the expected return. This paper investigates how dynamic correlations of stock markets change due to financial crisis and important global incidents.

Amongst others, Engle and Sheppard (2001) introduce the Dynamic Conditional Correlation (DCC) approach to investigate the time varying correlations between stock markets. Using the DCC model of Engle and Sheppard (2001), Wang and Moore (2008) study the interdependence of three CEE countries (the Czech Republic, Hungary, and Poland) with each other and with euro area markets and find that the latest financial crisis and the EU enlargement significantly increase the correlations of CEE countries both with each other and with euro area market. With a weekly data from 1997 to 2009, Syllignakis and Kouretas (2011) investigate the dynamic correlations between the stock markets of three major countries (Germany, Russia, and the US) and seven CEE countries (the Czech Republic, Estonia, Hungary, Poland, Romania, Slovakia and Slovenia). The authors reveal that due to more liberalized markets of the CEE countries (greater degree of financial openness and increased foreign investments) integration of those countries with major economies has increased in early 2000s, and recently the EU enlargement in 2004 has accelerated this process. By using the DCC model of Engle and Sheppard (2001), Kocenda and Egert (2011) examine the co-movements of the CEE countries (the Czech Republic, Hungary, and Poland) with developed countries (Germany, France, and the United Kingdom). Using an intraday data from June 2, 2003, 1:30 pm to February 9, 2005, 1:00 pm, however, they find very weak correlations among CEE countries, and between CEE countries and developed countries. On the other hand, the authors point out that the correlations among CEE markets have begun to increase in the second half of 2004 following the full membership of those countries into European Union.

However, since the DCC model of Engle and Sheppard (2001) is not able to capture the asymmetric effects in conditional correlations, Cappiello *et al.* (2006) introduce the Asymmetric Dynamic Conditional Correlation (ADCC) model that nests the DCC model and successfully captures the stronger impact of a negative shock on the correlation coefficients compared to a positive shock with same magnitude. Using a weekly data, Syriopoulos and Roumpis (2009) examine the stock markets of Balkan countries, Bulgaria, Cyprus, Croatia, Greece, Romania, and Turkey, and two of the leading mature countries Germany and the US for the period of April 27, 1998 to September 10, 2007. To investigate the co-movements, the volatility implications and the dynamic correlations among those stock markets, they employ constant conditional correlation model, dynamic conditional correlation model, and asymmetric dynamic conditional correlation model. The results reveal that mature markets have significant long-term impact on the stock markets of Balkan countries. Furthermore, conditional correlation models indicate the evidence of the absence of constant correlations and existence of asymmetric correlations among those stock markets. Kenourgios *et al.* (2009) provide evidence of integration in European stock markets over the period January 2, 1997 to October 1, 2006. Using structural breaks with the ADCC model, the authors investigate the impacts of important incidents such as internet bubble collapse and 2004 European Union enlargement on co-movements of stock markets of six developed countries in Euro area, six major CEE emerging countries, and two emerging Balkan countries. Test results reveal that the stock market dependence in Europe, in fact, presents symmetry. Furthermore, the results provide evidence that while the European financial integration is enhanced after the establishment of the EMU in 1999; there is structural increase in the level of dependence between all sample countries during the period of internet bubble burst in 2000, the introduction of the Euro banknotes and coins in 2002, and entry of CEE countries in EU in 2004. Employing the ADCC model, Gjika and Horvath (2012) examine time-varying stock market co-movements among CEE (the Czech Republic, Hungary, and Poland) countries. The results reveal that the correlation among CEE stock markets has gradually increased between 2001 and 2011, especially after the EU membership of those countries and the latest global financial crisis. Furthermore, the asymmetric dynamic conditional correlation analysis shows that the stock markets of CEE countries exhibit asymmetry in both conditional variances and conditional correlations. Therefore, the authors conclude that results suggest that diversification benefits among those countries disproportionally decrease during volatile periods due to asymmetric reactions to the shocks depending on the sign of the shock.

By using those two models with both symmetric and asymmetric volatility models (the GARCH model of Bollerslev (1986), the EGARCH model of Nelson (1991), the GJR-GARCH model of Glosten *et al*. (1993), and the APARCH model of Ding *et al.* (1993), we analyse the evolution of time-varying linkages between five emerging European countries and the world market. For this purpose, we identify four major events that have either global or regional effects; Russian crisis (1998), Dotcom crisis and 09/11 shock (2000-2002), EU accession of Central and Eastern European countries (2004 expansion), and Subprime mortgage crisis (2007-2009). In this context we are looking for answers for the following questions; do stock markets of emerging European countries exhibit asymmetry in conditional volatilities and/or in conditional correlation with the world market? Have emerging European stock markets and the world market become more correlated over time? Do the global financial crisis and other major events play any significant and joint role in driving the correlation structure of stock markets of emerging European countries with the world market?

Paper is organized as following. Data is described in section 2. Section 3 discusses the research methodology. Section 4 reveals the results obtained, and the last section concludes this work.

2. Data

For the period of January 01, 1996 to December 31, 2011, we collect daily observations of the main stock indices from the stock markets of emerging European countries; the PX of Prague Stock Exchange (the Czech Republic), the BUX of Budapest Stock Exchange (Hungary), the WIG20 of Warsaw Stock Exchange (Poland), the RTS of Russian Trading System Stock Exchange (Russia), and the XU100 of Istanbul Stock Exchange (Turkey), and the MSCI World Index as the proxy of the world market. Our sample period is selected so that it enables us to examine most of the important regional and global financial incidents after those countries actively opened their markets to foreign investors and started to seek for full liberalization. We obtain the daily data of closing prices of indices from DataStream, and transform by using Microsoft Excel, and estimate the empirical analyses by using software package E-Views 7.0.

In the first step, we convert all price series to logarithmic index returns by taking the first difference of natural log of daily closing prices:

$$R_{i,t} = \ln(I_{i,t}) - \ln(I_{i,t-1}), \tag{1}$$

where, $I_{i,t}$ is the index price of the i-th country at time t, $I_{i,t}$ is the index price of the i-th country at time $t-1$, and $R_{i,t}$ is the corresponding rate of return on index.

Preliminary step to examine the co-movement relationship between the variables is testing the stationarity of the series (Mahadeva and Robinson, 2004). As Harris (1995, p.1) perfectly summarizes “proceed to estimate a model containing non-stationary variables at best ignores important information about the underlying (statistical and economic) process generating the data, and at worst leads to nonsensical (or spurious) results”. Therefore, to check the presence of unit roots in return data, we apply two unit root tests, the Augmented Dickey-Fuller (ADF) test, and the Phillips-Perron (PP) test.

Table 1. Unit root tests results for stock indices

	ADF	PP
BUX	-61.34756*	-61.27261*
MSCI	-45.66381*	-56.36788*
PX	-59.05216*	-58.93530*
RTS	-56.91573*	-56.90762*
WIG20	-64.20609*	-64.20531*
XU100	-62.73988*	-62.75742*

Notes: The critical value for the ADF and PP test statistics for the given sample size (4175 observations) is -3.4317 at the 1% level. * denotes the rejection of the null hypothesis at 1% level.

Table 1 reports the results of ADF and PP tests for each return index. The null hypothesis for the ADF and PP tests is the presence of a unit root. As it can be seen on table, the statistic, t_α, for each index reveals that all index return series are found to be stationary since both ADF and PP tests clearly rejects the null of a unit root at the 1% level for the series.

3. Modelling Dynamic Conditional Correlations

To minimize the risk of inconsistent correlation estimates and to find the most suitable univariate GARCH model, in the first stage, we test different univariate GARCH models (GARCH model of Bollerslev (1986), Exponential GARCH model of Nelson (1991), GJR-GARCH model of Glosten *et al.* (1993), and Asymmetric Power ARCH model of Ding *et al.* (1993)) and select the one with the lowest SIC to standardise the residuals for the second stage. In the second stage, using the standardized residuals from univariate GARCH estimations, we estimate the DCC model of Engle and Sheppard (2001) and the ADCC model of Cappiello *et al.* (2006). For this stage, as it is done for the first stage, the bivariate dynamic conditional correlation model with the lowest SIC is selected to ensure to use the most optimal model for each time series.

3.1. Dynamic Conditional Correlation (DCC) Model

The DCC model of Engle and Sheppard (2001) is defined as:

$$r_{i,t}|F_{t-1} \sim N(0, H_t), \tag{2}$$

where, $r_{i,t}$ is normally distributed return series with zero mean, F_{t-1} is information set available at $t-1$, H_t is a positive definite conditional variance-covariance matrix. H_t can be decomposed as follows:

$$H_t = D_t R_t D_t \tag{3}$$

D_t is a 2×2 diagonal matrix of time-varying standard deviations from univariate GARCH models (the first step of the model) with $\sqrt{\sigma_{it}^2}$ on the i^{th} diagonal and can be expressed as follows:

$$D_t = \begin{bmatrix} \sqrt{\sigma_{11,t}^2} & 0 \\ 0 & \sqrt{\sigma_{22,t}^2} \end{bmatrix}. \tag{4}$$

R_t is a 2×2 time-varying correlation matrix that can be expressed as:

$$R_t = \begin{bmatrix} 1 & \rho_{12,t} \\ \rho_{21.t} & 1 \end{bmatrix}. \tag{5}$$

The elements in R_t can be calculated by using the following framework:

$$R_t = \left(diag(Q_t)\right)^{-1} Q_t \left(diag(Q_t)\right)^{-1}, \tag{6}$$

Q_t, the proposed dynamic correlation structure, can be expressed as:

$$Q_t = (1-\alpha-\beta)\bar{Q} + \alpha u_{t-1} u_{t-1}' + \beta Q_{t-1} \tag{7}$$

where u_t is the standardized residual matrix from the first stage estimation, and $\bar{Q}$ is the 2×2 unconditional variance-variance matrix of residuals, u_{it} .

In its full formation, the time-varying correlation coefficient can be written for a bivariate case as:

$$\rho_{12,t} = \frac{(1-\alpha-\beta)\bar{q}_{12} + \alpha u_{1,t-1} u_{2,t-1} + \beta q_{12,t-1}}{\sqrt{(1-\alpha-\beta)\bar{q}_{11} + \alpha u_{1,t-1}^2 + \beta q_{11,t-1}} \sqrt{(1-\alpha-\beta)\bar{q}_{22} + \alpha u_{2,t-1}^2 + \beta q_{22,t-1}}}. \tag{8}$$

Constraints of the Model: To guarantee a positive definite H_t for all t some simple conditions on the parameters should be imposed. According to this the estimated parameters α and β should satisfy the following conditions:

$$\begin{gathered} \alpha \geq 0 \; and \; \beta \geq 0, \\ \alpha + \beta < 1, \end{gathered} \tag{9}$$

and finally Q_t has to be positive definite.

3.2. Asymmetric Dynamic Conditional Correlation (ADCC) Model

In the dynamic conditional correlation estimator,Q_t,of DCC model of Engle and Sheppard (2001), "the correlation evolves according to a process with identical news impact and smoothing parameters for all pairs of variables" (Engle and Sheppard, 2001, p.541). However, this is very strong assumption and it is corrected by Cappiello *et al.* (2006) by modification of the estimator in a way that it captures the heterogeneity present in the data. Therefore, the main difference between the DCC and the ADCC model is related to how $Q_t$is modelled over time.

In the ADCC model of Cappiello *et al.* (2006),Q_t evolves as follows:

$$Q_t = (1-\alpha-\beta)\bar{Q} - \eta\bar{N} + \alpha u_{t-1}u_{t-1}^{'} + \beta Q_{t-1} + \eta n_{t-1}n_{t-1}^{'} \quad (10)$$

where,α,β, and η are estimated parameters, and η introduces the asymmetric effects into model ,u_t is the standardized residual matrix from the first stage estimation, $\bar{Q}$ is the 2×2 unconditional variance-covariance matrix of $u_t, n_t = l(u_t < 0)°u_t$ is the matrix of asymmetric shocks with $l(u_t < 0)$ being $1\times k$ indicator function that takes on the value 1 when $u_t < 0$ and 0 otherwise, ° denotes the Hadamard product, and $\bar{N}$ is the 2×2 unconditional variance-covariance matrix of n_t.

In its full formation, the time-varying correlation coefficient can be written for a bivariate case as:

$$\rho_{12,t} = \frac{(1-\alpha-\beta)\bar{q}_{12} - \eta\bar{n}_{12} + \alpha u_{1,t-1}u_{2,t-1} + \beta q_{12,t-1} + \eta n_{12,t-1}}{\sqrt{\{(1-\alpha-\beta)\bar{q}_{11} - \eta\bar{n}_{11} + \alpha u_{1,t-1}^2 + \beta q_{11,t-1} + \eta n_{11,t-1}\}}\sqrt{\{(1-\alpha-\beta)\bar{q}_{22} - \eta\bar{n}_{22} + \alpha u_{2,t-1}^2 + \beta q_{22,t-1} + \eta n_{22,t-1}\}}} \quad (11)$$

Constraints of the Model: Positive definiteness of H_t for all t some can be ensured by imposing of simple conditions on the parameters. According to this the estimated parameters α,β, and η should satisfy the following conditions:

$$\begin{gathered}\alpha \geq 0, \beta \geq 0, and\ \eta \geq 0, \\ \alpha + \beta + \delta\eta < 1,\end{gathered} \quad (12)$$

where, δ is the maximum eigenvalue that can be estimated on sample data as:

$$\bar{Q}^{-\frac{1}{2}}(\bar{N})\bar{Q}^{-\frac{1}{2}}. \quad (13)$$

Estimation of the Models: Assuming $\varepsilon_t|F_{t-1}\sim N(0,H_t)$, the log-likelihood function should be decomposed into two quasi-likelihood functions as volatility and correlation parts (Engle and Sheppard, 2001), where the first group of parameters is corresponding to the univariate GARCH parameters while the second group is corresponding to the dynamic correlation parameters.

$$\begin{gathered}GARCH: \emptyset = (\omega_1, \delta_1, \gamma_1, \ldots, \omega_n, \delta_n, \gamma_n) \\ DCC: \varphi = (\alpha, \beta) \\ ADCC: \varphi = (\alpha, \beta, \eta)\end{gathered} \quad (14)$$

To estimate those parameters, in the first step, the R_t matrix in the log likelihood function is replaced with the identity matrix I_k, which gives us the first stage quasi-likelihood function as following:

$$L_1(\emptyset|r_t) = -\frac{1}{2}\sum_{t=1}^{T}(mlog(2\pi) + 2\log|D_t| + \log|I_k| + \varepsilon_t^{'} D_t^{-1} I_k D_t^{-1}\varepsilon_t),$$
$$= -\frac{1}{2}\sum_{t=1}^{T}(mlog(2\pi) + 2\log|D_t| + \varepsilon_t^{'} D_t^{-2}\varepsilon_t)$$
$$= -\frac{1}{2}\sum_{t=1}^{T}\left(mlog(2\pi) + \sum_{t=1}^{m}\left(log(\sigma_{it}^2) + \frac{\varepsilon_{it}^2}{\sigma_{it}^2}\right)\right)$$
$$= -\frac{1}{2}\sum_{i=1}^{m}\sum_{t=1}^{T}\left(\log(2\pi) + \log(\sigma_{it}^2) + \frac{\varepsilon_{it}^2}{\sigma_{it}^2}\right) \quad (15)$$

Here, as it can easily be seen this first stage quasi-likelihood is the sum of individual GARCH likelihoods that we have explained in previous subsection. Thus, “maximizing the joint likelhood is equavilant to maximizing each univariate GARCH likelihood individually” (Gjika and Horvath, 2012, p.12). Now, by using the above function we estimate the parameters $\emptyset = (\omega_1, \delta_1, \gamma_1, \ldots, \omega_n, \delta_n, \gamma_n)$ for each univariate GARCH process.

In the second stage, we estimate $\varphi = (\alpha, \beta)$ for DCC model, and $\varphi = (\alpha, \beta, \eta)$ for ADCC model by conditioning on the estimated parameters $\widehat{\emptyset} = (\widehat{\omega}_1, \hat{\delta}_1, \hat{\gamma}_1, \ldots, \widehat{\omega}_n, \hat{\delta}_n, \hat{\gamma}_n)$ from step one.

$$QL_2^*(\varphi|\widehat{\emptyset}, r_t) = -\frac{1}{2}\sum_{t=1}^{T}(mlog(2\pi) + 2\log|D_t| + \log|R_t| + \varepsilon_t^{'} D_t^{-1} R_t D_t^{-1}\varepsilon_t)$$
$$= -\frac{1}{2}\sum_{t=1}^{T}(mlog(2\pi) + 2\log|D_t| + \log|R_t| + u_t^{'} R_t u_t) \quad (16)$$

“Given that we condition on the first stage parameters and after excluding the constant term as its first derivative with respect to correlation parameters is zero, the second step quasi-likelihood becomes” (Gjika and Horvath, 2012, p.12);

$$QL_2^*(\varphi|\widehat{\emptyset}, r_t) = -\frac{1}{2}\sum_{t=1}^{T}(\log|R_t| + u_t^{'} R_t^{-1} u_t) \quad (17)$$

And finally, parameters of the second step can be estimated with maximization of QL_2^* function.

4. Empirical Results

We reveal the results of dynamic conditional correlation analyses under four subsections as; investigation of the 1998 Russian financial crisis, investigation of the dotcom crisis and 9/11 shock, investigation of the EU accession of CEE countries, and investigation of the latest global financial crisis. The results reveal the detailed impacts of those global incidents on the return volatility of emerging European stock markets and the dynamic integrations of emerging European stock markets with the world market.

4.1. Investigation of the Russian Crisis

The first important incident for the region in terms of chronological order is the Russian crisis of 1998. Although Asian crisis hit the world few months before the Russian crisis; since it is not possible to separate the effects of those two crises due to a chronological closeness, here we only consider the impacts of the Russian crisis on the emerging European stock markets and the world market integrations. Forbes (2004) defines the Russian crisis as starting on August 17, 1998 “which is the date the government devalued the ruble and imposed a forced restructuring of its government date” (p.65), and lasting for 2 weeks. On the other hand Lucey and Voronkova (2008) claim that the crisis starts in October, 1997, and its impacts continue until December 1998. Therefore, to investigate the impacts of this incident, by following Forbes’s (2004) beginning date and Lucey and Voronkova’s (2008) end date, we separate our sample into three periods as shown in Table 2.

Table 2. Division of the sample period for the Russian crisis of 1998

	Observations	Corresponding date
Pre-crisis	1 to 688	01-01-1996 to 16-08-1998
Crisis	689 to 784	17-08-1998 to 31-12-1998
Post-crisis	785 to 1305	01-01-1999 to 31-12-2000

The results[1] reveal that during the pre-crisis period, except Prague Stock Exchange, the best fitted model to the return series is the GARCH model of Bollerslev (1986) for all of the stock markets. That indicates that, in the pre-crisis period, while negative and positive news create same effect on the volatility of the stock markets of Hungary, Poland, Russia and Turkey; the Czech Republic shows asymmetric volatility reactions. In other words, during the pre-crisis period, while positive and negative news create same level volatility in the stock markets of Hungary, Poland, Russia, and Turkey, the stock market of the Czech Republic shows stronger volatility to negative news compared to positive shocks that has same magnitude. During the crisis period, on the other hand, except for the Polish stock market, all the univariate models that are preferred by Schwarz Information Criterion are asymmetric ones. According to that, while Hungary prefers GJR-GARCH model, Turkey prefers EGARCH model, and the Czech Republic and Russia prefer APARCH model; Poland keeps GARCH model as pre-crisis period. Therefore, while one can say that Hungary, Russia and Turkey are negatively affected from the Russian crisis, since they become more sensitive to negative news and start to show higher volatility to negative news compared to positive news that has same magnitude; it is not possible to interpret the case of the Czech Republic since Prague Stock Exchange already shows asymmetric volatility reactions even during the pre-crisis period. On the contrary, Poland seems unaffected from the Russian crisis in terms of volatility reactions to the negative shocks since the crisis does not create any asymmetry on the volatility of Warsaw Stock Exchange and it keeps showing same level volatility reactions to both positive and negative news that have same magnitudes. Finally, after the crisis period, we see that countries lose that extra sensitivity to the negative shocks and start to show symmetric volatility to both negative and positive shocks, since for the post-crisis period GARCH model of Bollerslev (1986) is the best fitted univariate model for the residual series of all countries. The interesting point here is although the negative news creates higher volatility in the stock market of the Czech Republic before the crisis period, after the crisis period, this situation disappears and both positive and negative news start to create same level volatility in Prague Stock Exchange. As a result, we can briefly and simply conclude that Russian crisis creates a kind of panic or extra sensitivity towards negative news in the stock markets of Hungary, Russia, and Turkey. However, this extra sensitivity or over reaction to negative shocks disappears after the crisis period. Interestingly, Poland never gets panic and shows over volatility reaction to the negative shocks during the pre-crisis, crisis, and post-crisis periods, and the Czech Republic stops showing stronger volatility reactions to negative news after the crisis period.

According to bivariate dynamic conditional correlation analysis (Appendix, Table 2A), during the pre-crisis period, except the Russian stock market, DCC model of Engle and Sheppard (2001) is the best fitted model for all stock markets. That means, the dynamic correlation between the stock markets of the Czech Republic, Hungary, Poland, and Turkey and the world market is symmetrically affected by both positive and negative news. On the other hand, during the pre-crisis period, negative news affects the correlation of the Russian stock market with the world market stronger than positive news affects, i.e. integration between the Russian stock market and the world market increases more in the case of negative news compared to positive news. During the crisis period, while DCC model of Engle and Sheppard (2001) keeps being the best fitted model for the stock markets of CEE countries, the dynamic relations of the Russian and Turkish stock markets with the world market can be modelled best with the ADCC model of Cappiello *et al.* (2006). This result indicates that, during the crisis, in

[1] Table 1A, which fully presents the results, can be found in Appendix.

the case of bad news the correlation of those stock markets with the world market is higher than positive news of the same magnitude. Therefore, one can say that among emerging European countries, the Russian crisis of 1998 causes only Turkey to more strongly integrate with the world market in the case of negative news during the crisis period, since Russia already has an asymmetric correlation structure with the world market since the pre-crisis period. For the post-crisis period, the DCC model of Engle and Sheppard (2001) is the selected model for all of the sample countries. Therefore, we can say that after the crisis, although the dynamic correlation between the world market and the emerging European countries continues its presence, asymmetric impacts of news on the correlations of the Russian and Turkish stock markets with the world market do not exist anymore. This situation may show that markets are more confident compare to the crisis period and reacts more controlled to the negative news without any anxiety. That means, now, those stock markets do not immediately follow the negative movements of the world market. The biggest reason behind this situation may be the success of policy makers and the new regulations to make the financial markets stronger and more confident.

Table 3 exhibits the conditional correlation estimates between the emerging European stock markets and the world market for the pre-crisis, crisis, and post-crisis periods based on the selected bivariate DCC models. The results reveal that, all of the sample countries experience drastic decreases on their conditional correlations with the world market during the crisis period. Since the correlation levels of all of the sample countries significantly and jointly decrease during the crisis period, it possible to say that the Russian crisis is the trigger here that leads emerging European stock markets to temporarily disintegrate with the world market.

Table 3. Dynamic conditional correlation estimates for the Russian crisis of 1998 (period averages)

	BUX	PX	RTS	WIG20	XU100
Pre-crisis	0.2817	0.2652	0.2035	0.3242	0.2023
Crisis	0.1837	0.1047	0.0103	0.1612	0.0386
Post-crisis	0.3422	0.3126	0.2355	0.3266	0.1482

When we examine the post-crisis correlation levels, we see that the correlation levels of all emerging European stock markets are larger compared to their crisis period correlation levels, and some of them are even larger than the pre-crisis levels. Since the financial crisis causes these temporary segmentations of the regional markets from the world market (the MSCI World Index-24 developed countries), we reach a point that the 1998 Russian financial crisis is a regional financial crisis that particularly affect the emerging countries in the region, instead of a global financial crisis that jointly affects all global markets. Therefore, the analysis reveals that during that period, the stock markets of emerging European countries do not show similar movements with the rest of the world as much as they do during the pre-crisis period. As a result, in theory, the crisis period of the Russian crisis of 1998 could have been a good opportunity for international investors who wanted to diversify their portfolios with international stocks, since during that period the correlation between emerging European stock markets and the world market were much weaker compared to tranquil times.

4.2. Investigation of the Dotcom and 9/11 Crises

According to chronological order, the second important incident for whole world and the region is the Dotcom crisis. Therefore, in this section we investigate the impacts of the dotcom crisis on the process of stock market integrations of emerging European countries with the world market. Following table shows the division of our sample into three periods as; pre-crisis, crisis, and post-crisis. Here, it should be highlighted that the pre-crisis period is kept short due to the chronological closeness of the Russian crisis. Furthermore, our crisis period includes also another important but non-financial crisis, 9/11 shocks. Therefore, in this section we investigate the correlation between the stock markets of emerging European countries and the world market during the pre-Dotcom & 9/11 crises period, Dotcom & 9/11 crises period, and post-

Dotcom & 9/11 crises period. Among academics and practitioners it is widely believed that the Dotcom bubble bursts on March 10, 2000 when the NASDAQ peaks. While the impacts of the Dotcom crisis still continues on stock markets, America faces with another crisis, the 9/11 terrorist attacks, that creates another wave of financial shocks. Therefore, while we divide our sample period we use March 10, 2000 as the beginning of the crises, and assume that the joint impacts of the crises continue at least until the end of the year 2002. We separate our sample into three periods as shown in Table 4.

Table 4. Division of the sample period for the Dotcom and 9/11 crises

	Observations	Corresponding date
Pre-crisis	785 to 1094	01-01-1999 to 09-03-2000
Crisis	1095 to 1826	10-03-2000 to 31-12-2002
Post-crisis	1827 to 2350	01-01-2003 to 31-12-2004

For the pre-crisis period, the Schwarz Information Criterion chooses the GARCH model of Bollerslev (1986) for all of the sample countries (Appendix, Table 3A). That shows that after the Russian crisis period, emerging European countries enter a new period that they show symmetric volatility reactions to the news irrespective to the sign of the news. However, this period lasts with the arrival of another global financial crisis; dotcom crisis, and/or global political crisis; 9/11 crisis. According to that, during that period, global shocks or news start to create asymmetric effects on the volatility of stock exchanges of the Czech Republic, Hungary, and Russia. On the contrary, Turkey and Poland seem unaffected from this situation and keep showing symmetric volatility reactions to any kind of shocks. Therefore, since the Czech Republic, Hungary, and Russia start to show stronger volatility reactions to negative news during the crisis period, it can be said that dotcom and 9/11 crises create extra sensitivity and anxiety for those countries. Interestingly, as the Russian crisis period, the Polish stock market keeps calmness during the dotcom and 9/11 crises too and shows symmetric volatility reactions to both positive and negative news. Furthermore, unlike Russian crisis, this time the stock market of Turkey does not show any extra anxiety during the crisis and continues to show symmetric volatility reaction to both positive and negative news. Following the crisis period, extra sensitivity and over reaction to negative news continue in the Czech Republic, Hungary, and Russia. However, for more specific impacts of the crises on the volatility structures of stock markets, the parameter estimations of each stock market should also be interpreted.

The results of bivariate dynamic conditional correlation analyses (Appendix, Table 4A) reveal that for the pre-crisis period all of the sample countries prefer the DCC model of Engle and Sheppard (2001). This indicates that during the pre-crises period both positive and negative news generate same level impacts on the correlation of the stock markets of the sample countries with the world market. Furthermore, as it can be seen from the table, the crises do not create any changes on the balance between the impacts of negative news and positive news, during both crises and post-crises periods the DCC model of Engle and Sheppard (2001) is the best fitted model for all of the sample countries. According to this, even during the crises period the emerging European stock markets keep their calmness and do not tend to more strongly co-move with the world market in the case of negative news.

Finally, this symmetric dynamic conditional correlation structure does not change during the post-crises period too, and both positive and negative news continue to create same level impact on the correlation of emerging European stock markets with the world market.

Table 5. Dynamic conditional correlation estimates for the Dotcom and 9/11 crises (period averages)

	BUX	PX	RTS	WIG20	XU100
Pre-crisis	0.3322	0.3076	0.2305	0.3216	0.1432
Crisis	0.3544	0.3242	0.2887	0.3481	0.1208
Post-crisis	0.2486	0.2632	0.2806	0.3193	0.1822

Table 5 presents period averages of the daily conditional national stock market-world market correlation estimates based on the selected bivariate DCC models during, pre-crisis, crisis, and post-crisis periods. During the crisis period, among the sample countries, the stock markets of the Czech Republic, Hungary, and Poland show slight increase on their correlation levels. However, the interesting point here is that all three countries experience sharp decreases on their integration levels with the world market during the post-crisis period. The only reason of this situation can be an incident that affects all those three countries at the same time during that post-crisis period. Since our post-crisis period does include the EU accession period of those three Central and Eastern European countries, it is highly possible that decreases on the stock market-world market correlations take places due to that incident. In the next section, we investigate the EU accession of those countries in detail to see the specific impacts of the 2004 EU expansion on the integration levels of emerging European stock markets with the world market. Although for Turkey and Russia the case is slightly different, it is still clear that the Dotcom and 9/11 crises do not create any dramatic impact on the integration levels of the stock markets of those countries with the world market. While the Russian stock market experiences a slight increase during the crisis period as the CEE countries, after the crises period unlike those countries it does not show any significant change. On the other hand, unlike other emerging European countries, the integration level of the Turkish stock market slightly decreases during the crisis period and significantly increases after the crisis period. Since, the sample countries do not significantly follow a joint trend during any of the periods; it is not possible to conclude whether the dotcom and 9/11 crises significantly increase or decrease the integration levels of the emerging European stock markets. However, we are still able to conclude that the dotcom crisis and 9/11 shocks do not have any significant impact on the portfolio diversification strategies of the international investors, since they do not significantly change the correlation levels of the equities from emerging European countries with the world market.

4.3. Investigation of the EU Enlargement of 2004

In the fourth step of our analysis, we investigate the impact of the EU enlargement of 2004 on the integration structure of emerging European stock markets with the world market. The accession negotiations with the candidate countries ended in December 2002, and full accession date of 10 candidate countries is announced as May 1, 2004. Since we believe that any significant effect may occur right after the announcement of the news of full accession-before the actual accession takes place-, we divide our sample into three periods as; pre-announcement period, post-announcement period, and post-accession period. According to this, while post-announcement period comprises the period from the announcement of future accession of the CEE countries into EU to actual accession date, post-accession date comprises the period after the full accession date. Table 6 presents how we divide our sample period into three periods.

Table 6. Division of the sample period for the EU enlargement of 2004

	Observations	Corresponding date
Pre-Announcement	987 to 1814	01-01-2000 to 12-12-2002
Post-Announcement	1815 to 2153	13-12-2002 to 31-03-2004
Post-Accession	2154 to 2882	01-05-2004 to 31-12-2006

During the period of January 1, 2000 - December 12, 2002, except for Hungary, both positive and negative news create same level volatility for all sample countries. In that pre-announcement period the volatility reactions of the stock markets of the Czech Republic, Poland, Russia, and Turkey can be explained best with the GARCH model of Bollerslev (1986) while the GJR-GARCH model of Glosten *et al.* (1993) is the best fitted model for the return series of the Hungarian stock market. Our second period starts with the announcement of the acceptance of the Czech Republic, Hungary, and Poland as full members of European Union and ends with the full accession of those countries to the EU. As it can be seen in Table 5A in

Appendix, during that post-announcement period while the best fitted models for all other countries stand same as symmetric GARCH model, there is a change for Hungary. During the pre-announcement period while the best fitted model is GJR-GARCH model of Glosten *et al.* (1993) for the Hungarian stock market, for the post-announcement period the GARCH model of Bollerslev (1986) is the best fitted one. Therefore, since the stock market of Hungary starts to show same level volatility reactions to both positive and negative news that have same magnitude, this change can be interpreted as the end of the anxiety in Budapest Stock Exchange towards negative news, probably thanks to the announcement of EU membership. Up to that point nothing is surprising in results since occurrence of an asymmetry on volatility of stock markets due to EU membership was not expected. Hungary's special condition, asymmetric volatility reaction before the announcement and symmetric reaction after the announcement, is also quite logical since the announcement of EU membership may create confidence for investors and this situation may eliminate the extra sensitivity towards the bad news. However, the results of the post-accession period are quite interesting and surprising. The univariate GARCH model analysis of this period reveals that, while the volatility reactions of all newly accepted European Union countries, the Czech Republic, Hungary, and Poland can be explained best by a symmetric model during the post-accession period, the GARCH model of Bollerslev (1986), the volatility reactions of Turkey and Russia can be modelled best with an asymmetric univariate model, the GJR-GARCH model of Glosten *et al.* (1993). Therefore, it is possible to say that the stock markets of Turkey and Russia are significantly affected from the full accession of their counterparts, since while they used to give same level reactions to both negative and positive news during the pre-announcement and post-announcement periods; after the full accession of those newly acquired CEE countries, bad news starts to cause higher volatility than good news. This interesting result can be interpreted as; the EU memberships of their counterparts may have created an extra sensitivity to negative news for the Turkish and Russian stock markets. However, this situation may likely to occur also due to own internal financial and political dynamics of countries. Therefore, the stronger reactions of the Turkish and Russian stock markets to negative news compared to positive news that have same magnitude cannot be surely said that occur only due to the full EU memberships of the Czech Republic, Hungary, and Poland.

Table 7 reports period averages of the daily conditional national stock market-world market correlation estimates based on the selected bivariate DCC models. Although univariate GARCH model estimation gives some interesting results, results of bivariate DCC model is pretty straight forward (Appendix, Table 6A). According to that, for all investigated periods all of the sample countries prefer the DCC model of Engle and Sheppard (2001). That means, announcement of the EU membership of the Czech Republic, Hungary, and Poland and full accession of those countries into EU do not affect the dynamic conditional correlation structure between emerging European countries and the world market. The dynamic correlations between emerging European stock markets and the world market are still symmetrically affected by positive and negative news after the announcement and accession. Thus, we conclude that although the accession of CEE countries into EU creates asymmetry in the volatility of Istanbul Stock Exchange and Russian Trading System Stock Exchange, the conditional correlations between those stock markets and the world market are still symmetric.

Table 7. Dynamic conditional correlation estimates for the EU enlargement of 2004 (period averages)

	BUX	PX	RTS	WIG20	XU100
Pre-Announcement	0.3517	0.3199	0.2777	0.3439	0.1062
Post-Announcement	0.2546	0.2682	0.2734	0.3189	0.1742
Post-Accession	0.2557	0.2711	0.2615	0.3254	0.2546

During the post-announcement period, the stock markets of the Czech Republic, Hungary, and Poland follow similar trends and all of them experience decreases on the correlation levels. While the integration levels slightly decrease for the Czech and Polish stock markets, the Hungarian stock market strongly separates from the world market during that period. The reason behind this temporary separation may possibly be a new investment trend among international investors towards those newly acquired EU countries. In other words, the announcement of the full membership may have increased the confidence of the investors to those markets and this situation may have caused temporary separations of those markets from the world market. Baltzer *et al.* (2008) clearly state that during the post-accession period, compared to the pre-accession period, significant increases on the integration levels of the newly acquired countries are expected. However, since our sample period is not divided as pre-accession and post-accession periods, we are not able to compare the post-accession period with the pre-accession period. During the post-accession period, however, we do not see any significant changes on the correlation levels compared to the post-announcement period. This insignificant change from the post-announcement period to the post-accession period can be explained with the division of the sample period. According to this, it is highly possible that our post-accession period does not cover the period that the integration levels start to increase. Our full period analysis, in fact, proves the validity of this reasoning since, on year-based analysis we can clearly see that from 2006 onwards the integration levels of the CEE countries with the world market continuously increase.

On the other hand, during the post-announcement and post-accession periods, Russia and Turkey follow different patterns. While the stock market of Russia does not experience any significant or remarkable changes and does not follow any certain trend, Turkey has some interesting significant changes. It seems the announcement of the future membership of the Czech Republic, Hungary and Poland significantly increases the integration level of the stock market of Turkey with the world market. However, as we remember from the full period analysis part, since Turkey has already been following a steady increasing trend since 2001, the increase that we observe during the post-accession and post-announcement periods may have arisen due to internal, country-specific reasons/trends.

As a result, it is possible to conclude that since the EU membership announcement creates temporary but long term segmentation (although the integration levels start to increase in the post-accession period, they are still lower than the pre-announcement period) of the CEE countries from the world market, it was a good opportunity for international investors to diversify their portfolios with stocks from those specific countries. On the other hand, since the Turkish stock market increases its integration level during those periods, a diversification strategy with Turkish stocks would not provide any additional benefits to international investors.

4.5. Investigation of the Subprime Mortgage Crisis

The latest important incident for whole world and the region is the global financial crisis that started as subprime mortgage crisis in the United States. Therefore, here we call one of the heaviest global financial crises in history with its original name. As we do for other crises, we investigate this crisis also in three periods; pre-crisis period, crisis period, and post-crisis period. Although there are different opinions about the exact date of each period, for the beginning date of the crises we follow Naoui *et al.* (2010) by supposing the explosion of the subprime bubble occurred on August 1, 2007. Similarly, while identifying the end date of the crisis, we benefit from the literature and use March 31, 2009 by following Manda (2010). Table 8 exhibits the assumptions regarding the period dates.

Table 8. Division of the sample period for the subprime mortgage crisis

	Observations	Corresponding date
Pre-crisis	2351 to 3022	01-01-2005 to 31-07-2007
Crisis	3023 to 3457	01-08-2007 to 31-03-2009
Post-crisis	3458 to 4175	01-04-2009 to 31-12-2011

From the beginning of 2005 to the assumed beginning date of the crisis (August 1, 2007), both positive and negative news create same magnitude impacts on the volatility of the stock markets of the Czech Republic, Hungary and Poland, while negative news create more drastic impacts compared to the same magnitude positive news on the volatility of Turkish and Russian stock markets. That results show that even before the crisis Turkey and Russia are so sensitive to the negative news. Ali *et al.* (2010) clearly express that during crisis times stock markets tend to overreact to negative news. Therefore, the results of the crisis period are as expected since during that period the return volatilities of all of the sample countries can be better estimated with asymmetric univariate models. As Table 7A (Appendix) reports GJR-GARCH model is the selected univariate GARCH model for the crisis period for all of the sample countries. Before conducting analysis for the subprime crisis we have investigated two other crises; the Russian financial crisis and the dotcom & 9/11 crises. During those crises we observe changes on the best fitted univariate models and see that for most of the countries while the preferences are symmetric models during the pre-crisis periods, with the effect of a crisis those preferences change to asymmetric ones. And again, for most of the cases, after the impacts of crisis disappear, those countries' volatility reactions can again be modelled best with the symmetric univariate GARCH model. However, results reveal that the situation is different this time. Although we assume that the subprime crisis lasts quite long and we leave almost 2 years for the crisis period, still during the post-crisis period, except the Czech Republic, all the sample countries show asymmetric volatility reactions to negative news. That shows us that although we are in the post-crisis period, which means the toughest part of the crisis is over, the markets are still not so confident and extremely sensitive to the negative news. Thus, they still overreact to negative news compared to positive news that has same magnitude. We can interpret this situation in two ways; either the crisis is not over yet or the fear of the crisis still exists among investors.

For bivariate dynamic conditional correlation models, except Russian Stock Exchange for the post-crisis period, all of the sample stock markets for all the periods prefer DCC model of Engle and Sheppard (2001) (Appendix, Table 8A). That means only Russia, only during post-crisis period, integrates with the world market more strongly in the case of negative news, while integration levels of all other sample countries give symmetric reactions to both positive and negative news during all examined periods.

Table 9 presents the conditional correlation between national stock markets and the world market for pre-crisis, crisis, and post-crisis periods. During the crisis period, we observe drastic increases on the correlations for all sample countries. Therefore, it is fair to say that the subprime mortgage crisis has caused emerging European stock markets to become more integrated with the world market. Furthermore, we see that these increases on the correlation levels are not temporary since during the post-crisis period the conditional correlations either continue to increase or correct themselves with slight decreases.

Table 9. Dynamic conditional correlation estimates for the subprime mortgage crisis (period averages)

	BUX	PX	RTS	WIG20	XU100
Pre-crisis	0.3033	0.3387	0.3219	0.3973	0.3524
Crisis	0.4685	0.4991	0.4864	0.5471	0.5113
Post-crisis	0.4647	0.4961	0.5818	0.5317	0.4744

After the crisis period, while the stock markets of the Czech Republic, Hungary, and Turkey experience slight decrease on their correlation levels with the world market, the stock markets of Russia and Poland start to have even stronger correlations with the world market. There may be two potential reasons behind this permanent stronger integration; either financial crisis still continues or it has permanently changed the structure of the world finance and created more integrated national markets. We know that although the global financial crisis which started in 2007 has lost its globally destructive impact in late 2009 and early 2010, it has caused another wave of shocks that propagated among developed European countries. Therefore, this secondary crisis may have been the reason of the strong correlations during the post-crisis period. Alternatively, again it is well known fact that, 2007-2009 (the subprime mortgage crisis) global financial crisis is one of the most dramatic financial crisis ever (Helleiner, 2011; Reinhart and Rogoff, 2011). Thus, it is highly possible that the heavy crisis conditions may have caused permanent changes on the international finance and make stock markets more dependent to other international markets. However, to clearly examine the post-crisis period and to observe the new world after that destructive crisis, there is a need for longer sample period. Nevertheless, it is still fair to say that the global financial crisis of 2007-2009 has created more integrated national stock markets with the world markets that are sensitive to all news from other countries, and ultimately has caused the potential benefits of portfolio diversification strategies with those countries to weaken.

5. Conclusion

It is obvious that each analysed global/regional event impacts the sample countries differently according to the internal dynamics of those countries. However, these results can still be generalized to provide useful insights to predict the impacts of future similar incidents on the volatilities of stock markets and their correlations with the world market. According to that, we see that financial crises either regional (the Russian crisis) or global (the dotcom and 9/11 shocks, and the subprime mortgage crisis) create extra sensitivities on the emerging European stock markets and lead those markets to react more strongly to negative news (asymmetric volatility effects). Furthermore, events that lead to economical and/or political progress of countries (the EU Accession of the Czech Republic, Hungary, and Poland) create asymmetry on the volatility of the stock markets of their counterparts (Russia and Turkey). On the other hand, generalizing the impacts of the investigated incidents on correlation levels is not as straightforward as generalizing the impacts on volatility reactions. For instance while the Russian crisis of 1998 significantly decreases the integration levels of emerging European countries with the world market, and the dotcom and 9/11 crises do not create any significant changes on the dynamic conditional correlations, the subprime mortgage crisis causes drastic increases on the integration levels. However, it is still possible to conclude that the correlation levels of the stock markets of emerging European countries with the world market increase in case of really disruptive global financial crisis, and decrease in case of regional crisis. Therefore, our analyses confirm that portfolio diversification strategies should be dynamic as conditional levels, and by observing the previous incidents international investors should predict the potential impacts of those incidents on the integration levels of those countries with other markets/world market and modify their portfolios accordingly.

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Appendix

Table 1A. Selected univariate GARCH model parameter estimation results for the Russian crisis of 1998

	Selected Model	ω	α	γ	β	λ	Logl	SIC
				Pre-Crisis				
BUX	GARCH	0.0000*	0.2286*	-	0.6387*	-	1781.85	-5.419
		(2.42)	(2.60)		(6.32)			
PX	APARCH	0.0061	0.1894*	0.3316*	0.8069*	0.0713*	2242.82	-6.798
		(1.02)	(2.79)	(3.29)	(7.39)	(4.39)		
RTS	GARCH	0.0000	0.2077*	-	0.7642*	-	1391.70	-4.226
		(1.56)	(2.96)		(9.04)			
WIG20	GARCH	0.0000	0.1185*	-	0.7958*	-	1695.12	-5.146
		(1.55)	(2.15)		(8.35)			
XU100	GARCH	0.0000*	0.0877*	-	0.8702*	-	1497.33	-4.549
		(2.18)	(2.36)		(18.18)			
				Crisis				
BUX	GJR-GARCH	0.0000	0.0452	0.1588*	0.9478*	-	254.98	-3.989
		(1.04)	(0.99)	(2.42)	(15.99)			
PX	APARCH	0.0000*	0.0412*	0.1144*	0.9494*	0.0436*	377.13	-6.025
		(5.74)	(3.86)	(2.33)	(22.27)	(10.98)		
RTS	APARCH	0.1152	0.2177*	0.3104*	0.7070*	0.0000*	216.06	-3.345
		(0.80)	(2.15)	(1.99)	(5.38)	(9.94)		
WIG20	GARCH	0.0000	0.1611	-	0.8225*	-	249.81	-3.944
		(1.11)	(2.28)*		(11.15)			
XU100	EGARCH	-0.0685	-0.1561	0.2138*	0.9704*	-	220.25	-3.424
		(-0.53)	(-0.92)	(5.70)	(107.59)			
				Post-Crisis				
BUX	GARCH	0.0000*	0.1646*	-	0.8269*	-	1402.03	-5.366
		(17.89)	(9.60)		(7.26)			
PX	GARCH	0.0000	0.1376*	-	0.7925*	-	1497.32	-5.744
		(1.41)	(2.93)		(9.39)			
RTS	GARCH	0.0001	0.1071*	-	0.7921*	-	1043.23	-3.984
		(1.57)	(2.82)		(8.53)			
WIG20	GARCH	0.0000	0.0828*	-	0.8088*	-	1352.71	-5.176
		(2.03)*	(2.91)		(15.49)			
XU100	GARCH	0.0002	0.1902*	-	0.6046*	-	1042.24	-3.987
		(1.93)*	(2.25)		(3.89)			

Notes: ω; constant term,γ; the coefficient for leverage effects, λ; the power parameter of the standard deviation for APARCH model, and α(news coefficient) and β(lag coefficient); parameters that determine the short-run dynamics of volatility series. Numbers in parentheses are t-statistics.* indicates significance at %5 level.

This table reports the parameter estimates of the selected univariate GARCH models for the stock return series from January 1, 1996 to December 31, 2000 under three different periods. The GARCH model of Bollerslev (1986), the EGARCH model of Nelson (1991), the GJR-GARCH model of Glosten *et al.* (1993), and the APARCH model of Ding *et al.* (1993) are estimated with one lag of innovation, one lag of volatility, one order of asymmetry (where applicable). Then the models with the lowest Schwarz information criterion (SIC) are employed to get standardized residuals.

Table 2A. Selected bivariate DCC model parameter estimation results for the Russian crisis of 1998

	Selected Model	α	β	η	Logl	SIC
			Pre-Crisis			
BUX	DCC	0.0044 (1.85)	0.9015* (17.21)	-	-634.47	1.963
PX	DCC	0.0322* (2.78)	0.8760* (16.60)	-	-652.46	2.015
RTS	ADCC	0.0133* (2.64)	0.9514* (48.97)	0.0660* (3.55)	-640.96	1.992
WIG20	DCC	0.0072 (1.01)	0.9791* (40.58)	-	-632.69	1.954
XU100	DCC	0.0479* (1.97)	0.8516* (10.21)	-	-647.88	2.004
			Crisis			
BUX	DCC	0.0508* (2.31)	0.9490* (4.46)	-	-111.47	1.906
PX	DCC	0.0463* (3.03)	0.9334* (3.89)	-	-108.74	1.675
RTS	ADCC	0.0162* (3.31)	0.9050* (4.87)	0.0191* (5.12)	-103.49	1.814
WIG20	DCC	0.1417* (0.67)	0.7471 (1.10)	-	-110.50	1.905
XU100	ADCC	0.0246* (2.89)	0.9609* (2.31)	0.0190* (4.81)	-113.80	1.983
			Post-Crisis			
BUX	DCC	0.0194 (1.53)	0.9594* (32.18)	-	-495.69	1.938
PX	DCC	0.0150* (3.66)	0.9201* (5.16)	-	-497.71	1.949
RTS	DCC	0.0930* (2.69)	0.9066* (2.11)	-	-494.41	1.933
WIG20	DCC	0.0165* (2.46)	0.9720* (4.71)	-	-490.05	1.916
XU100	DCC	0.0027* (1.99)	0.9085* (13.05)	-	-515.80	2.019

Notes: α and β are common parameters of both DCC and ADCC model, while η is ADCC specific parameter. The significance of both α and β indicate the existence of dynamic conditional correlation between two samples while significant parameter, η, shows that dynamic correlation is asymmetric. Numbers in parentheses are t-statistics.* indicates significance at %5 level.

This table reports the parameter estimates of the selected bivariate DCC model. DCC (1,1) model of Engle and Sheppard (2001) and the ADCC (1,1,1) of Cappiello *et al.* (2006) are estimated using the standardized residuals from the first stage estimation. The DCC model with the lowest Schwarz information criterion (SIC) is selected to estimate time varying conditional correlations.

Table 3A. Selected univariate GARCH model parameter estimation results for the Dotcom and 9/11 crises

	Selected Model	ω	α	γ	β	λ	Logl	SIC
				Pre-Crisis				
BUX	GARCH	0.0000* (2.54)	0.0402* (16.71)	-	0.9282* (12.52)	-	821.60	-5.279
PX	GARCH	0.0000 (1.02)	0.1407* (2.80)	-	0.7672* (5.27)	-	911.09	-5.860
RTS	GARCH	0.0001 (1.17)	0.0394* (3.10)	-	0.8653* (8.89)	-	700.80	-3.845
WIG20	GARCH	0.0000 (1.65)	0.0466* (3.81)	-	0.8902* (8.13)	-	720.01	-5.230
XU100	GARCH	0.0000 (3.31)*	0.1443* (2.56)	-	0.8460* (6.41)	-	803.12	-4.675
				Crisis				
BUX	GJR-GARCH	0.0000* (2.46)	0.1675* (2.74)	0.2988* (2.26)	0.6515* (6.06)	-	1901.23	-5.172
PX	GJR-GARCH	0.0000* (2.62)	0.0313 (1.73)	0.1558* (3.90)	0.8992* (31.31)	-	2105.49	-5.732
RTS	GJR-GARCH	0.0000* (2.01)	0.0404 (1.01)	0.1294* (2.05)	0.8437* (11.18)	-	1754.30	-4.770
WIG20	GARCH	0.0000 (1.62)	0.0438 (1.86)	-	0.9121* (22.09)	-	1945.81	-5.303
XU100	GARCH	0.0002* (3.27)	0.2153* (3.11)	-	0.5769* (6.26)	-	1501.71	-4.087
				Post-Crisis				
BUX	GJR-GARCH	0.0000 (0.83)	0.0414 (1.47)	0.1611* (2.98)	0.8785* (7.39)	-	1632.10	-6.217
PX	GJR-GARCH	0.0000* (2.70)	0.0576* (4.23)	0.1897* (2.73)	0.6666* (5.50)	-	1708.80	-6.499
RTS	GJR-GARCH	0.0000* (2.03)	0.1006* (3.86)	0.2015* (3.11)	0.7170* (12.32)	-	1516.32	-5.553
WIG20	GARCH	0.0000 (1.66)	0.0409* (2.36)	(0.1634)* (2.21)	0.9113* (16.11)	-	1339.41	-6.126
XU100	GARCH	0.0000 (1.46)	0.1602* (2.13)	-	0.9009* (20.63)	-	1294.22	-7.147

Notes: ω; constant term,γ; the coefficient for leverage effects, λ; the power parameter of the standard deviation for APARCH model, and α(news coefficient) and β(lag coefficient); parameters that determine the short-run dynamics of volatility series. Numbers in parentheses are t-statistics.* indicates significance at %5 level.

This table reports the parameter estimates of the selected univariate GARCH models for the stock return series from January 1, 1999 to December 31, 2004. The GARCH model of Bollerslev (1986), the EGARCH model of Nelson (1991),the GJR-GARCH model of Glosten *et al.* (1993), and the APARCH model of Ding *et al.* (1993) are estimated with one lag of innovation, one lag of volatility, one order of asymmetry (where applicable). Then the models with the lowest Schwarz information criterion (SIC) are employed to get standardized residuals.

Table 4A. Selected bivariate DCC model parameter estimation results for the Dotcom and 9/11 crises

	Selected Model	α	β	η	Logl	SIC
			Pre-Crisis			
BUX	DCC	0.0329* (3.17)	0.9434* (20.20)	-	-300.7625	1.996
PX	DCC	0.0084* (4.27)	0.9304* (5.72)	-	-310.7116	2.061
RTS	DCC	0.0372 (1.54)	0.7981* (2.89)	-	-300.5200	1.995
WIG20	DCC	0.0237* (2.56)	0.8390* (2.56)	-	-288.8895	1.919
XU100	DCC	0.0106* (3.04)	0.8183* (7.71)	-	-296.6732	1.616
			Crisis			
BUX	DCC	0.0203* (2.86)	0.8984* (5.96)	-	-729.9632	2.020
PX	DCC	0.0895* (2.46)	0.8731* (4.05)	-	-691.5133	1.915
RTS	DCC	0.0107* (2.56)	0.7227 (0.83)	-	-693.0715	1.919
WIG20	DCC	0.0635 (1.93)	0.9051* (3.06)	-	-686.5623	1.901
XU100	DCC	0.0032* (3.33)	0.9796* (14.14)	-	-719.7279	1.992
			Post-Crisis			
BUX	DCC	0.0111* (3.18)	0.9025* (8.01)	-	-506.9811	1.982
PX	DCC	0.0239* (2.30)	0.9396* (15.88)	-	-503.8401	1.958
RTS	DCC	0.0446* (2.94)	0.9291* (11.24)	-	-514.6706	1.929
WIG20	DCC	0.0375* (2.01)	0.9421* (9.96)	-	-501.4113	1.889
XU100	DCC	0.0174* (3.02)	0.9441* (13.55)	-	-512.1208	2.009

Notes: α and β are common parameters of both DCC and ADCC model, while η is ADCC specific parameter. The significance of α and β indicates the existence of dynamic conditional correlation between two samples, while significant parameter, η, shows that dynamic correlation is asymmetric. Numbers in parentheses are t-statistics.* indicates significance at %5 level.

This table reports the parameter estimates of the selected bivariate DCC model. DCC (1,1) model of Engle and Sheppard (2001) and the ADCC (1,1,1) of Cappiello *et al.* (2006) are estimated using the standardized residuals from the first stage estimation. The DCC model with the lowest Schwarz information criterion (SIC) is selected to estimate time varying conditional correlations.

Table 5A. Selected univariate GARCH model parameter estimation results for the EU enlargement of 2004

	Selected Model	ω	α	γ	β	λ	Logl	SIC
				Pre-Announcement				
BUX	GJR-GARCH	0.0000* (2.45)	0.0720* (3.50)	0.1431* (2.47)	0.8938* (30.48)	-	2854.129	-5.525
PX	GARCH	0.0000* (2.03)	0.0603* (3.75)	-	0.8520* (18.08)	-	2967.605	-5.753
RTS	GARCH	0.0000* (2.08)	0.0704* (3.89)	-	0.9031* (41.03)	-	2299.070	-4.452
WIG20	GARCH	0.0000* (2.67)	0.0914* (3.92)	-	0.7718* (21.13)	-	2448.131	-5.213
XU100	GARCH	0.0000* (2.91)	0.0798* (4.03)	-	0.9096* (15.32)	-	2657.013	-5.621
				Post-Announcement				
BUX	GARCH	0.0000* (4.08)	0.0609* (2.56)	-	0.6779* (7.85)	-	1055.648	-6.213
PX	GARCH	0.0000 (1.45)	0.0575* (3.10)	-	0.6974* (3.73)	-	1109.941	-6.535
RTS	GARCH	0.0000* (2.15)	0.0702* (2.39)	-	0.9008* (5.21)	-	1334.851	-6.984
WIG20	GARCH	0.0000 (1.17)	0.0811* (3.15)	-	0.6634* (3.96)	-	1214.457	-6.341
XU100	GARCH	0.0000* (3.23)	0.0895* (2.23)	-	0.9012* (4.49)	-	1079.453	-5.948
				Post-Accession				
BUX	GARCH	0.0000 (1.87)	0.0707* (3.18)	-	0.6621* (17.32)	-	2577.462	-5.922
PX	GARCH	0.0000* (3.73)	0.0536* (2.62)	-	0.7090* (13.62)	-	2800.803	-6.429
RTS	GJR-GARCH	0.0000* (2.64)	0.1199* (3.58)	0.1679* (2.73)	0.9004* (17.40)	-	2404.432	-5.515
WIG20	GARCH	0.0000 (1.55)	0.0835* (2.85)	-	0.6716* (47.15)	-	2614.357	-6.007
XU100	GJR-GARCH	0.0012* (2.64)	0.1629* (2.78)	0.1413* (4.13)	0.9015* (15.52)	-	2383.373	-5.466

Notes: ω; constant term,γ; the coefficient for leverage effects, λ; the power parameter of the standard deviation for APARCH model, and α(news coefficient) and β(lag coefficient); parameters that determine the short-run dynamics of volatility series. Numbers in parentheses are t-statistics.* indicates significance at %5 level.

This table reports the parameter estimates of the selected univariate GARCH models for the stock return series from January 1, 1999 to July 31, 2007. The GARCH model of Bollerslev (1986), the EGARCH model of Nelson (1991),the GJR-GARCH model of Glosten *et al.* (1993), and the APARCH model of Ding *et al.* (1993) are estimated with one lag of innovation, one lag of volatility, one order of asymmetry (where applicable). Then the models with the lowest Schwarz information criterion (SIC) are employed to get standardized residuals.

Table 6A. Selected bivariate DCC model parameter estimation results for the EU enlargement of 2004

	Selected Model	α	β	η	Logl	SIC
		Pre-Announcement				
BUX	DCC	0.0224* (2.78)	0.9435* (24.75)	-	-961.493	1.885
PX	DCC	0.1153* (3.03)	0.8766* (2.29)	-	-981.298	1.924
RTS	DCC	0.0829* (2.86)	0.8466 (0.57)	-	-983.734	1.929
WIG20	DCC	0.0431 (1.47)	0.8714* (3.31)	-	-974.321	1.894
XU100	DCC	0.0648* (2.04)	0.8435* (8.63)	-	-992.654	2.023
		Post-Announcement				
BUX	DCC	0.0277* (2.58)	0.8172* (2.41)	-	-347.878	2.105
PX	DCC	0.0165* (4.77)	0.9313* (7.85)	-	-338.160	2.047
RTS	DCC	0.0298* (2.59)	0.8960* (5.11)	-	-339.113	2.501
WIG20	DCC	0.0135* (2.69)	0.9012* (6.03)	-	-376.251	2.412
XU100	DCC	0.0312* (3.61)	0.8779* (4.45)	-	-391.416	2.305
		Post-Accession				
BUX	DCC	0.0430* (2.67)	0.8075* (5.66)	-	-838.731	1.952
PX	DCC	0.0157* (2.12)	0.9787* (90.15)	-	-810.701	1.887
RTS	DCC	0.0371* (2.11)	0.9200* (20.24)	-	-824.708	1.920
WIG20	DCC	0.0095* (3.20)	0.9815* (63.23)	-	-805.288	1.875
XU100	DCC	0.0202 (1.56)	0.9355* (18.95)	-	-812.601	1.892

Notes: α and β are common parameters of both DCC and ADCC model, while η is ADCC specific parameter. The significance of α and β indicates the existence of dynamic conditional correlation between two samples while significant parameter, η, shows that dynamic correlation is asymmetric. Numbers in parentheses are t-statistics.* indicates significance at %5 level.

This table reports the parameter estimates of the selected bivariate DCC model. DCC (1,1) model of Engle and Sheppard (2001) and the ADCC (1,1,1) of Cappiello *et al.* (2006) are estimated using the standardized residuals from the first stage estimation. The DCC model with the lowest Schwarz information criterion (SIC) is selected to estimate time varying conditional correlations.

Table 7A. Selected univariate GARCH model parameter estimation results for the subprime mortgage crisis

	Selected Model	ω	α	γ	β	λ	Logl	SIC
				Pre-Crisis				
BUX	GARCH	0.0000 (1.69)	0.0644* (2.44)	-	0.8744* (16.18)	-	1958.400	-5.816
PX	GARCH	0.0000* (1.99)	0.0862* (2.66)	-	0.8105* (14.11)	-	1909.413	-5.515
RTS	GJR-GARCH	0.0000* (2.14)	0.0458* (2.88)	0.1313* (2.68)	0.7764* (12.92)	-	1902.110	-5.639
WIG20	GARCH	0.0000* (2.41)	0.0713* (3.67)	-	0.9201* (9.97)	-	1867.601	-5.919
XU100	GJR-GARCH	0.0009* (2.22)	0.1908* (2.52)	0.1704* (4.24)	0.8093* (10.59)	-	1851.536	-5.488
				Crisis				
BUX	GJR-GARCH	0.0000 (1.25)	0.0578* (2.37)	0.1319* (2.50)	0.8861* (28.48)	-	1118.332	-5.193
PX	GJR-GARCH	0.0000* (2.20)	0.0605* (3.30)	0.1846* (2.19)	0.8336* (21.75)	-	1129.769	-5.186
RTS	GJR-GARCH	0.0000 (1.45)	0.0563 (1.72)	0.1725* (1.99)	0.8613* (23.00)	-	987.3641	-4.578
WIG20	GJR-GARCH	0.0005* (2.70)	0.0604 (1.85)	0.1378* (4.63)	0.9348* (147.78)	-	1091.263	-4.995
XU100	GJR-GARCH	0.0000* (2.23)	0.0951* (2.27)	0.1091* (2.74)	0.8748* (70.73)	-	1036.358	-4.741
				Post-Crisis				
BUX	GJR-GARCH	0.3430* (2.03)	0.1411* (3.06)	0.0485* (3.31)	0.8507* (53.98)	-	1899.896	-5.285
PX	GARCH	0.0000* (2.06)	0.1400* (2.74)	-	0.8465* (17.09)	-	2108.849	-5.879
RTS	GJR-GARCH	0.0000 (1.93)	0.0607 (0.05)	0.0564* (2.58)	0.8709* (69.32)	-	1850.557	-5.154
WIG20	GJR-GARCH	0.0000* (4.00)	0.0462* (5.01)	0.0732* (7.49)	0.9141* (19.60)	-	2049.2220	-5.703
XU100	GJR-GARCH	0.0000* (2.28)	0.0438 (1.05)	0.1209* (2.70)	0.8728* (9.29)	-	1986.795	-5.528

Notes: ω; constant term,γ; the coefficient for leverage effects, λ; the power parameter of the standard deviation for APARCH model, and α(news coefficient) and β(lag coefficient); parameters that determine the short-run dynamics of volatility series. Numbers in parentheses are t-statistics.* indicates significance at %5 level.

This table reports the parameter estimates of the selected univariate GARCH models for the stock return series from January 1, 2005 to December 31, 2011. The GARCH model of Bollerslev (1986), the EGARCH model of Nelson (1991), the GJR-GARCH model of Glosten *et al.* (1993), and the APARCH model of Ding *et al.* (1993) are estimated with one lag of innovation, one lag of volatility, one order of asymmetry (where applicable). Then the models with the lowest Schwarz information criterion (SIC) are employed to get standardized residuals.

Table 8A. Selected bivariate DCC model parameter estimation results for the subprime mortgage crisis

	Selected Model	α	β	η	Logl	SIC
			Pre-Crisis			
BUX	DCC	0.0100 (1.15)	0.9802* (4.01)	-	-638.2262	1.927
PX	DCC	0.0394* (2.03)	0.9166* (6.67)	-	-641.3980	1.916
RTS	DCC	0.0413* (2.15)	0.9092* (17.76)	-	-624.3717	1.886
WIG20	DCC	0.0294* (1.99)	0.8621* (8.81)	-	-671.3907	1.773
XU100	DCC	0.0388 (1.29)	0.8229* (4.81)	-	-616.4875	1.862
			Crisis			
BUX	DCC	0.0191* (2.77)	0.9339* (8.99)	-	-356.3178	1.705
PX	DCC	0.0045* (3.81)	0.8727* (6.61)	-	-337.5748	1.598
RTS	DCC	0.0179* (2.98)	0.9447* (12.55)	-	-365.1184	1.746
WIG20	DCC	0.0175 (0.47)	0.8277 (0.93)	-	-356.0075	1.680
XU100	DCC	0.0203* (2.64)	0.9820* (9.12)	-	-351.8760	1.660
			Post-Crisis			
BUX	DCC	0.0697 (1.74)	0.9226* (2.06)	-	-566.5345	1.607
PX	DCC	0.0278* (2.17)	0.9025* (12.69)	-	-584.1567	1.657
RTS	ADCC	0.1865* (2.71)	0.8053 (1.33)	(0.2297)* (3.07)	-504.4506	1.444
WIG20	DCC	0.0038* (2.39)	090016* (3.49)	-	-534.7341	1.518
XU100	DCC	0.0765* (2.43)	0.8563* (7.17)	-	-605.5621	1.717

Notes: α and β are common parameters of both DCC and ADCC model, while η is ADCC specific parameter. The significance of α and β indicates the existence of dynamic conditional correlation between two samples, while significant parameter, η, shows that dynamic correlation is asymmetric. Numbers in parentheses are t-statistics.* indicates significance at %5 level.

This table reports the parameter estimates of the selected bivariate DCC model. DCC (1,1) model of Engle and Sheppard (2001) and the ADCC (1,1,1) of Cappiello *et al.* (2006) are estimated using the standardized residuals from the first stage estimation. The DCC model with the lowest Schwarz information criterion (SIC) is selected to estimate time varying conditional correlations.