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# Does Global Financial Crisis Causes Financial Contagion Effects on European Stock Markets?

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**Abstract**

This paper studies the impact of the global financial crisis contagion across European stock markets. For this research, we selected seven European stock markets and picked up the period between 04/10/1999 and 30/06/2011. To identify the occurrence of contagion effect, we used the multivariate dynamic conditional correlation (DCC) developed by Engle (2002), and tests the average correlation coefficients, estimated by the DCC model in order to understand if coefficients recorded in the global financial crisis sub-period differ from those recorded in the previous sub-periods. The analysis revealed that the correlation coefficients increased significantly in the last sub-period, which confirms the existence of contagion effects among stock markets studied.

**Keywords:** Global Financial Crises, International Stock Markets, Contagion Effects, DCC-GARCH.
**JEL Classification Codes:** G01, G15

## 1. Introduction

The global economy has witnessed profound and rapid changes, deepening the economic and financial interdependence among countries, reflected in the increasing flows of goods, services and capital across borders. According to Fabozzi (1995), technological developments, institutionalization and liberalization of financial markets contributed to the globalization of financial markets, which have helped to create conditions for contagion.

In the last decade several episodes of crisis have marked the financial markets. The two most important episodes of crisis was dot-com and the global financial crisis, triggered in the U.S., in the subprime sector, which was considered as the *first* and most severe global crisis since the Great

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Depression (Claessens *et al.*, 2010; Bekaert *et al.*, 2011; Lin and Treichel, 2012). Although this crisis had its origin in the United States, in the subprime credit sector, would affect the global stock markets.

The concept of contagion has been one of the most debated topics in international finance literature, especially since the financial crisis of 1987. Although there is, in financial literature, an effective consensus on this concept, most authors associate contagion with financial crisis propagation. In this study we follow the definition of Forbes and Rigobon (2002), to study the existence of contagion between markets. Several methodologies have been applied to study this phenomenon among markets. Methodologically this study uses the bivariate DCC-GARCH model, since according to authors such as Engle (2002), Tse and Tsui (2002), and Tsay (2002), it improves the quality of contagion tests, compared with results produced from non-conditional correlation coefficients. In terms of structure, this investigation continues in Section 2 with a literature review, in section 3 with the description of the data and methodology, in 4 with the presentation of empirical results and 5 with the presentation of the abstract and main findings.

## 2. Literature Review

As already mentioned, the concept of contagion has attracted the attention of several authors, but there is no consensus about it. Calvo and Reinhart (1996) define financial contagion as the transmission of a financial crisis to a certain country, as a result of their financial links with countries that experienced an episode of financial crisis. Park and Song (2000) define contagion as the propagation of disturbances from one market to another market. King and Wadhwani (1990), Calvo and Reinhart (1996) and Collins and Biekpe (2003), argue that financial contagion is observed by intensifying the correlations between financial markets, during periods of turbulence or financial crisis. Most studies concerning the change in patterns of correlation in financial markets as an element that confirms the occurrence of contagion. Eichengreen and Rose (1998) and Glick and Rose (1999) have a broader definition, which includes the transmission of shocks between economies, through various channels of contagion. Masson (1999), Van Rijckeghem and Weder (2001) and Rigobon (2003) have a narrower definition of contagion, considering only specific transmission channels and exacerbated shocks. According to the authors, the simultaneous movement of economic variables, in turbulent times, is a symptom of contagion. Lin *et al.* (1994) associate the concept of contagion to the transmission of financial assets price volatility from a country living a financial crisis to other countries. A stylized fact, commonly referred in financial markets literature, is the increasing volatility in periods of financial turmoil. In this sense, the crisis can be identified with periods of extreme volatility; the contagion is verified considering the spillover volatility from one market to another. Moreover, while assets' price volatility is related to market uncertainty, contagion is associated with increased uncertainty among financial markets. According to Forbes and Rigobon (2002), a more consensual definition assigned to the term contagion is a significant increase in the degree of international co-movements in stock price indices, after a shock in one country or group of countries. In this sense, after a shock, if two markets exhibit high correlation, this is not necessarily contagion. Contagion is associated with a significant change in the correlation. These authors use, then, the term shift-contagion to differentiate their definition.

To examine the links between markets and to study contagion episodes, several studies have resorted to the Dynamic Conditional Correlation (DCC-GARCH).

Wang *et al.* (2006) applied a bivariate DCC-GARCH model to study the impact of the Asian financial crisis on the Chinese economy. The empirical results show positive conditional correlation coefficients and co-movements between the Thai market and the Chinese market. The Asian financial crisis had a significant impact on the stock markets. In various stock markets, the variances recorded higher values in the post-crisis period than in the pre-crisis period and the average conditional correlation coefficient on post-crisis period increased significantly, revealing evidence of financial contagion. Chiang *et al.* (2007) applied the DCC-GARCH model to study the dynamics of correlation among nine Asian stock markets in the period from $1^{th}$ January 1990 to $21^{th}$ March 2003. These authors sensed a strong increase in the correlations of the studied indices, since the second half of 1997 until early 1998, which corresponded to the emergency phase of the crisis, which was interpreted as a contagion effect, followed by a herding effect. Egert and Kocenda (2007), using a bivariate DCC-GARCH model, detected a strong correlation between the German market and the French market, and between these and the UK market, from June 2003 to January 2006. In contrast, a weak but positive, correlation was detected, between the French index and three markets of Central and Eastern Europe. Kenourgios *et al.* (2007) applied the asymmetric generalized dynamic conditional correlation model (AG-DCC) to look for correlations of stock markets of four emerging markets, namely Brazil, Russia, India and China, with the US and UK markets, during periods of negative shocks. This model provided empirical evidence in favor of high dependency in periods of asset prices fall. On the other hand, when bad news arrive to markets, conditional correlations between the four emerging markets and the developed markets increased sharply. Cappiello *et al.* (2006) have investigated the possibility of asymmetries in the correlation dynamics between asset classes and market conditions, since 1987 to 2002, using the AG-DCC model. The findings of this study revealed that negative shocks have more impact than positive ones. Research also has extended DCC-GARCH model to the financial risk management. Lee *et al.* (2006) have implemented the DCC model to assess the Value-at-Risk of a portfolio. In this study, a portfolio was considered, comprising representative national stock market indices for the G7 countries, with equal weighting for each of them. The DCC-GARCH model was used to predict VaR, in terms of 1 and 10 days. In both cases, the DCC model showed better results than the simple moving average and exponential weighted moving average models. This study confirms the use of DCC-GARCH as a predictive tool beyond the customary use as an evaluation tool.

## 3. Data and Methodology

### 3.1. Data

Aiming to detect contagion between the European stock markets, the dataset comprises of daily stock price index in Germany (DAX 30), France (CAC 40), UK (FTSE 100), Spain (IBEX 35), Ireland (ISEQ Overall), Greece (ATG) and Portugal (PSI 20). The data used in this study were obtained from Econostats and cover the period from 4th October 1999 to 30th June 2011, which, in turn, was subdivided into three sub-periods. To analyze the Dot-Com Crisis the sub-period between 04/10/1999 to 31/03/2003 was chosen. For the latest episode of crisis, which began with the U.S. subprime credit crisis, the day of 01/08/2007 was considered as the date of emergence. For many authors, including Horta *et al.* (2008), Toussaint (2008), and Naoui *et al.* (2010), this day was seen as the time when the financial markets were surprised by the subprime crisis, with the rising rates of Credit Default Swaps. In addition to the sub-periods of crisis, a third sub-period was also considered, designated quiet sub-period, between 01/04/2003 and 31/07/2007, which corresponded to a bull market period. In this study, the data has been transformed into daily stock returns using logarithmic transformation such as $\ln(P_t/P_{t-1})$, where $P_t$ and $P_{t-1}$ representing the closing values of a particular index at time $t$ and $t-1$, respectively.

### 3.2. Methodology

#### 3.2.1. Dynamic Conditional Correlation Model

The present study relies on dynamic conditional correlation model (DCC-GARCH), proposed by Engle (2002) and Tse and Tsui (2002), which distinguishes itself from other models, such as the conditional correlation constant proposed by Bollerslev (1990), considering a time-varying conditional correlation matrix, and incorporating the possibility of the correlation between two assets change over time.

The estimation of this model involves two phases. In the first phase, a univariate GARCH model is estimated for the individual time series. In the second phase, the standardized residuals, obtained from the previous phase, are used to obtain the conditional correlation.

In the DCC-GARCH model the conditional covariance matrix is expressed as:

$$ {}_t = D_t \Gamma_t D_t \tag{1}$$

$$D_t = diag\left(\sqrt{h_{11,t}}, \sqrt{h_{22,t}}, \ldots, \sqrt{h_{nn,t}}\right) \tag{2}$$

$$\Gamma_{t+1} = \; diag\left(Q_t\right)^{-1/2} Q_t \;\; diag\left(Q_t\right)^{-1/2} \tag{3}$$

$$Q_t = \left(1-\alpha-\beta\right)\overline{Q} + \alpha u_{t-1} u'_{t-1} + \beta Q_{t-1} \tag{4}$$

where: $h_{it}$ follows the GARCH (1, 1) process, $\Sigma_t$ is the conditional covariance matrix and $u_t$ is a vector of standardized values of t. $\Gamma_t$ denoting the time varying correlation matrix and $Q_t$ is the positive definite symmetric matrix. $\overline{Q}$ expresses the unconditional variance matrix of $u_t$. The time varying elements of $\Gamma_t$, $\rho_{ij,t}$ are:

$$\rho_{ij,t} = \frac{q_{ij,t}}{\sqrt{q_{ii,t} + q_{jj,t}}} \tag{5}$$

where: $q_{ij,t}$ is the element of $Q_t$. For the positive definiteness of $\Gamma_t$, the $Q_t$ matrix needs to be positive definite. $\alpha \geq 0$, $\beta \geq 0$ and $\alpha + \beta < 1$ are conditions to be satisfied by the conditional correlation matrix that will be positive definite.

The parameter estimation of the DCC model is carried out using conditional maximum likelihood estimation. Under the assumption of normally distributed errors, parameters can be estimated by maximizing the following log likelihood function:

$$L\left(\theta\right) = -\frac{1}{2} {}_{i=1}^{T} \; n \log 2\pi + 2\log\left|D_t\right| + \log\left(\Gamma_t\right) + u'_t \Gamma_t^{-1} u_t \tag{6}$$

### 3.2.2. Tests for Equality of Means

To test the consistency of the correlation coefficients between the various dynamic markets in “Dot-Com”, “Quiet” and “Global Financial Crisis” sub-periods, and finally conclude about the existence of contagion effect, we use the t-test. The null and alternative hypotheses are:

$$H_{01} : \mu_{GlobalCrisis} = \mu_{Dot-Com} \text{ e } H_{02} : \mu_{GlobalCrisis} = \mu_{Quiet} \tag{7}$$

$$H_{a1} : \mu_{GlobalCrisis} \neq \mu_{Dot-Com} \text{ e } H_{a2} : \mu_{GlobalCrisis} \neq \mu_{Quiet} \tag{8}$$

Where $\mu_{Dot-Com}$, $\mu_{Quiet}$ e $\mu_{GlobalCrisis}$ are the average conditional correlation coefficients in Dot-Com, Quiet and Global Financial Crisis sub-periods.

The test statistic is given by:

$$t = \frac{\left(\overline{\mu}_{Global\ \mathrm{Crisis}} - \overline{\mu}_{Dot-Com\ \ or\ \mathrm{Quiet}}\right) - \left(\mu_{Global\ \mathrm{Crisis}} - \mu_{Dot-Com\ \ or\ \mathrm{Quiet}}\right)}{\dfrac{S^2_{Global\ \mathrm{Crisis}}}{n_{Global\ \mathrm{Crisis}}} + \dfrac{S^2_{Dot-Com\ \ or\ \mathrm{Quiet}}}{n_{Dot-Com\ \ or\ \mathrm{Quiet}}}^{\frac{1}{2}}} \tag{9}$$

where $S^2$ is the variance of the conditional correlation coefficients and $n$ is the sample size. The number of degrees of freedom, ν, of the Student's t distribution is given by:

$$v = \frac{\dfrac{S^2_{GlobalCrisis}}{n_{GlobalCrisis}} + \dfrac{S^2_{Dot-Com\ \ or\ \mathrm{Quiet}}}{n_{Dot-Com\ \ or\ \mathrm{Quiet}}}^{2}}{\dfrac{S^2_{GlobalCrisis}}{n^2_{GlobalCrisis}\left(n_{GlobalCrisis}-1\right)} + \dfrac{S^2_{Dot-Com\ \mathrm{or}\ Quiet}}{n^2_{Dot-Com\ \ or\ \mathrm{Quiet}}\left(n_{Dot-Com\ \ or\ \mathrm{Quiet}}-1\right)}} \tag{10}$$

## 4. Empirical Results

The main descriptive statistics of the daily rates of return of the seven indices in full period and in each of the three sub-periods are presented in Tables 1 and 2 (the last in the Appendix). The analysis of the descriptive statistics allows the conclusion that only in the quiet sub-period all indices showed positive average daily returns. Moreover, all series returns showed signs of deviation from normality assumption, since the test Jarque-Bera reject this hypothesis, and the coefficients of skewness and kurtosis are statistically different from a normal distribution3. On the other hand, during the full period four indices showed negative asymmetry.

**Table 1:** Descriptive statistics summary in the full period

| | ATG | CAC | DAX | FTSE | IBEX | ISEQ | PSI |
|---|---|---|---|---|---|---|---|
| Mean | -0,0005 | -0,0001 | 0,0001 | 0,0000 | 0,0000 | -0,0002 | -0,0001 |
| Stand. Dev. | 0,0167 | 0,0156 | 0,0162 | 0,0130 | 0,0153 | 0,0150 | 0,0117 |
| Skewness | -0,1547 | 0,0421 | 0,0618 | -0,1053 | 0,0471 | -0,6522 | -0,2240 |
| Kurtosis | 7,0 | 8,0 | 7,2 | 9,1 | 9,5 | 11,1 | 13,0 |
| Jarque-Bera | 1917,3 | 2974,3 | 2138,9 | 4528,5 | 5170,5 | 8059,5 | 12085,0 |
| Prob. | 0,0000 | 0,0000 | 0,0000 | 0,0000 | 0,0000 | 0,0000 | 0,0000 |
| ADF | 0,0000 | 0,0000 | 0,0000 | 0,0000 | 0,0000 | 0,0000 | 0,0000 |
| ARCH-LM | 25,0 | 37,6 | 43,1 | 51,1 | 26,7 | 49,5 | 31,3 |
| Prob. | 0,0000 | 0,0000 | 0,0000 | 0,0000 | 0,0000 | 0,0000 | 0,0000 |

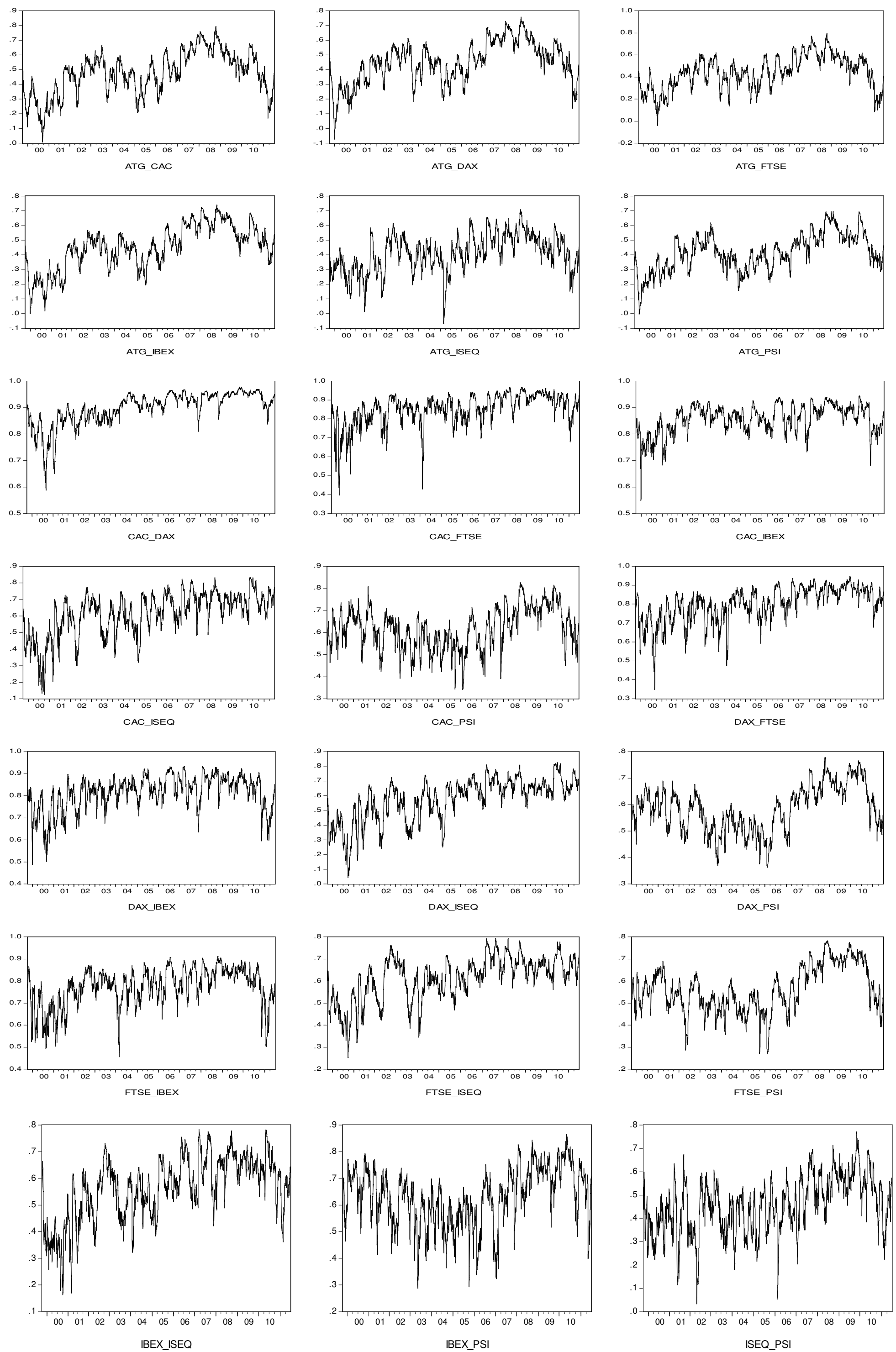
With the aim to test the stationarity of the series of returns, the ADF test was applied. The null hypothesis states that the series had a unit root, ie, that the series were integrated of order 1, given the alternative hypothesis that the series had no unit root. The results of testing the stationarity, in the three sub-periods, are shown on Table 2, in the appendix. In all cases, the ADF test statistics are smaller than the significance level of 1%, rejecting the null hypothesis of integration, so we can conclude that the series of returns are stationary.

Figure 1, in the appendix, shows the series of daily returns of the seven indices in the full period. The analysis of returns shows that volatility is concentrated in certain periods. The second sub-period, running from 2003 to 2007, was relatively calm, compared to the other sub-periods. However, the remaining sub-periods showed great turbulence and volatility, suggesting that the returns are grouped in clusters of volatility. In the analyzed full period, the year 2008 showed greater volatility as a result of the global financial crisis. The existence of conditional heteroskedasticity (ARCH effects) in the series of returns was confirmed by the Lagrange multiplier (LM) test for ARCH, proposed by Engle (1982), which was applied to a first-order autoregressive process. The results of these tests are presented in tables 1 and 2 (the second in the appendix). The use of the DCC-GARCH model is justified by the presence of conditional heteroskedasticity in the return data, to analyze the possible significant increase in correlation between markets.

Table 3, in the Appendix, presents the parameter estimates of the DCC-GARCH models. All the $\alpha$ and $\beta$ parameters are statistically different from zero and respect the non-negativity condition. Additionally, in all bivariate models the sum of the parameters is close to unity $(\alpha + \beta < 1)$. Thus the bivariate DCC models are appropriate. This means that the volatility generating process is stable, shows a high degree of persistence and the conditional correlations are time varying. Figure 2 shows the evolution of the dynamic conditional correlations of the various country pairs. There was a clear increase in conditional correlations, due to the emergence of the global financial crisis, which reflects an increasing co-movement between the European stock markets. In several pairs of indices, the conditional correlations recorded in the last sub-period are greater than 90%, similarly to DAX-CAC and DAX-FTSE pairs.

[3] In the case of a normal distribution, skewness and kurtosis are equal to zero and three, respectively.

**Figure 2:** Dynamic conditional correlations




Aiming to test if the correlations, between each market and each of the remaining six markets, are consistent in the three sub-periods, tables 4 and 5 (the last presented in the appendix) show the t-statistics values. If the correlation coefficients are significant and the null hypothesis is rejected, then there is contagion effect. If the correlation coefficients are significant and the null hypothesis is not rejected, there is a relationship of interdependence.

**Table 4:** Testing the effect of contagion between the Global Financial Crisis sub-period and the quiet sub-period (observed values for t)

| | **CAC** | **DAX** | **FTSE** | **IBEX** | **ISEQ** | **PSI** |
|---|---|---|---|---|---|---|
| ATG | 380,640 (0,000) | 353,543 (0,000) | 251,998 (0,000) | 982,343 (0,000) | 197,905 (0,000) | 1192,698 (0,000) |
| CAC | | 327,727 (0,000) | 533,431 (0,000) | 62,933 (0,000) | 576,130 (0,000) | 1679,638 (0,000) |
| DAX | | | 721,664 (0,000) | 1,811 (0,179) | 519,629 (0,000) | 2776,408 (0,000) |
| FTSE | | | | 80,295 (0,000) | 612,811 (0,000) | 2707,695 (0,000) |
| IBEX | | | | | 354,508 (0,000) | 1740,060 (0,000) |
| ISEQ | | | | | | 977,309 (0,000) |

**Note:** values between parentheses show probability values, rejecting H0 if p-value<0.05.

Table 4 shows the t-test values, for the effect contagion between the global financial crisis sub-period and the previous sub-period. All the conditional correlations coefficients indicated a significant increase in the last sub-period, except for the DAX-IBEX pair, which points out that there was contagion between these markets. In turn, the t-test results, presented in Table 5, which analyzed the first and third sub-periods, conclude that in all cases there was an increase in conditional correlations.

## 5. Summary and Conclusions

In this paper, we have studied the current financial crisis, which, according to many authors, is the most severe financial crisis after the Great Depression and the first global financial crisis the world has known. In order to understand the impact of the crisis on contagion among European stock markets, we analyzed seven markets and considered the period between 10/04/1999 and 30/06/2011, which was divided into three sub-periods, one corresponding to the Dot-Com crisis, another corresponding to a bull market, and finally one that corresponds to the global financial crisis. To estimate the correlation between markets, we applied the bivariate DCC-GARCH model, developed by Engle (2002). To test the contagion effect, we applied tests for equality of means, following the methodology proposed by Forbes and Rigobon (2002). The findings confirm that during the global financial crisis sub-period, the conditional correlation between different European markets experienced a significant increase, compared with the previous two sub-periods. In relation to the first sub-period, all correlation coefficients increased significantly, at a significance level of 1%. Over the second sub-period, only the DAX-IBEX pair of correlation didn´t increase with statistical significance, so it was possible to see that the global financial crisis led to a contagion effect among European stock markets.

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# Appendix

**Figure 1:** Returns evolution during the full period

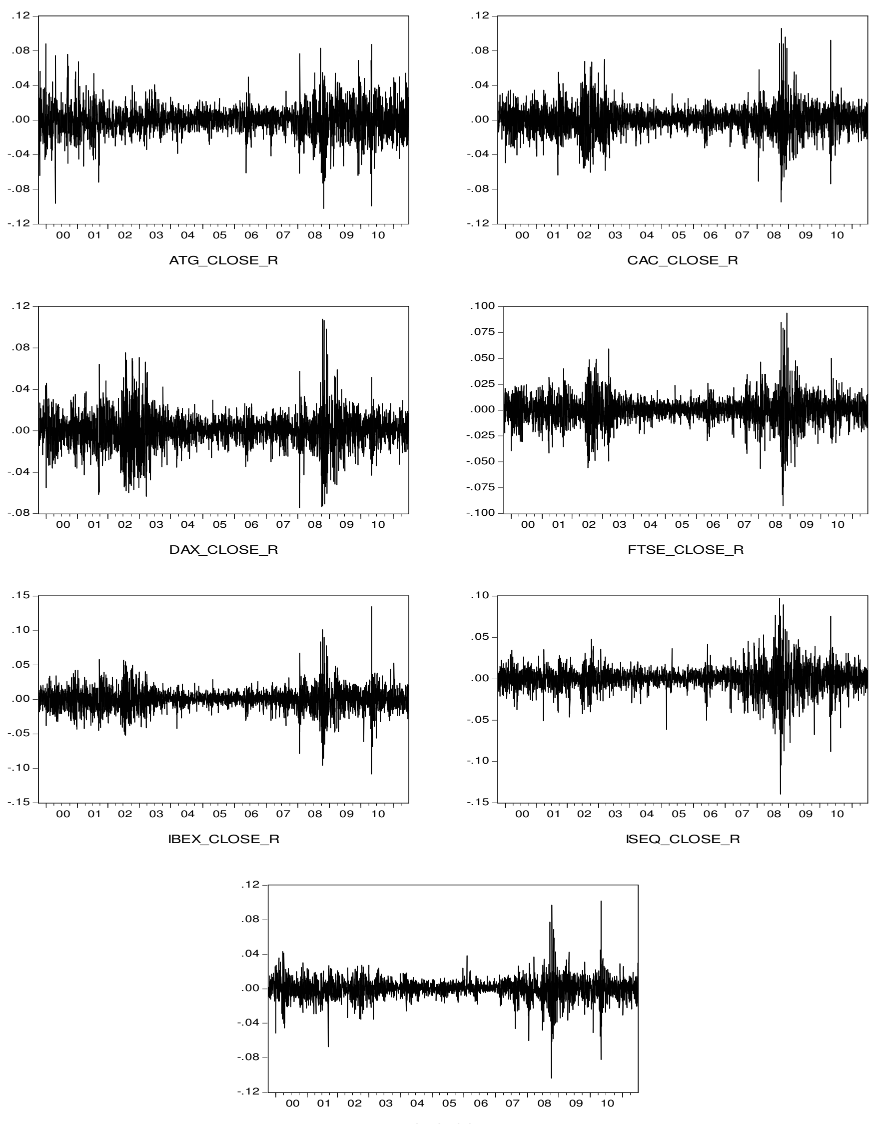

**Table 1:** Descriptive Statistics, Jarque-Bera, ADF and ARCH-LM test results in each sub-period

| | | ATG | CAC | DAX | FTSE | IBEX | ISEQ | PSI |
|---|---|---|---|---|---|---|---|---|
| **Dot-Com** | Mean | -0,00159 | -0,00067 | -0,00090 | -0,00061 | -0,00058 | -0,00023 | -0,00077 |
| | Stand. Dev. | 0,01732 | 0,01848 | 0,02034 | 0,01450 | 0,01706 | 0,01226 | 0,01199 |
| | Skewness | 0,19667 | 0,07598 | 0,08432 | -0,04717 | 0,12481 | -0,32263 | -0,35467 |
| | Kurtosis | 6,86158 | 4,15651 | 4,04117 | 4,37674 | 3,32982 | 4,54360 | 5,06416 |
| | Jarque-Bera | 532,35163 | 48,07453 | 39,30778 | 67,28602 | 6,04498 | 98,90022 | 168,32593 |
| | Prob. | 0,00000 | 0,00000 | 0,00000 | 0,00000 | 0,00000 | 0,00000 | 0,00000 |
| | ADF | 0,00000 | 0,00000 | 0,00000 | 0,00000 | 0,00000 | 0,00000 | 0,00000 |
| | ARCH-LM | 4,78582 | 9,62223 | 11,02103 | 10,55689 | 6,23767 | 5,33018 | 3,63347 |
| | Prob. | 0,00000 | 0,00000 | 0,00000 | 0,00000 | 0,00000 | 0,00000 | 0,00000 |
| **Quiet** | Mean | 0,00088 | 0,00056 | 0,00082 | 0,00045 | 0,00074 | 0,00061 | 0,00070 |
| | Stand. Dev. | 0,00974 | 0,00852 | 0,00925 | 0,00696 | 0,00798 | 0,00870 | 0,00582 |
| | Skewness | -0,51602 | -0,26161 | -0,27716 | -0,35941 | -0,33769 | -0,87734 | 0,13243 |
| | Kurtosis | 6,14263 | 4,03048 | 3,70569 | 4,99718 | 4,59264 | 9,48970 | 5,98635 |
| | Jarque-Bera | 377,92700 | 46,13575 | 27,81510 | 155,62450 | 103,37060 | 156,11140 | 310,47510 |
| | Prob. | 0,00000 | 0,00000 | 0,00000 | 0,00000 | 0,00000 | 0,00000 | 0,00000 |
| | ADF | 0,00000 | 0,00000 | 0,00000 | 0,00000 | 0,00000 | 0,00000 | 0,00000 |
| | ARCH-LM | 9,84627 | 4,24381 | 9,16237 | 7,09474 | 3,35463 | 3,20455 | 1,89414 |
| | Prob. | 0,00000 | 0,00000 | 0,00000 | 0,00000 | 0,00000 | 0,00000 | 0,01010 |
| **Global Financial Crisis** | Mean | -0,00139 | -0,00038 | -0,00003 | -0,00007 | -0,00037 | -0,00110 | -0,00062 |
| | Stand. Dev. | 0,02110 | 0,01827 | 0,01694 | 0,01621 | 0,01898 | 0,02136 | 0,01539 |
| | Skewness | -0,14016 | 0,14445 | 0,21786 | -0,04249 | 0,12892 | -0,45098 | -0,02445 |
| | Kurtosis | 5,02526 | 8,65830 | 9,57230 | 8,71452 | 9,82585 | 7,23413 | 11,02768 |
| | Jarque-Bera | 169,30040 | 1300,04100 | 1757,08900 | 1322,85000 | 1889,68000 | 759,02620 | 2610,06300 |
| | Prob. | 0,00000 | 0,00000 | 0,00000 | 0,00000 | 0,00000 | 0,00000 | 0,00000 |
| | ADF | 0,00000 | 0,00000 | 0,00000 | 0,00000 | 0,00000 | 0,00000 | 0,00000 |
| | ARCH-LM | 7,97466 | 13,56396 | 17,42443 | 18,01107 | 7,84351 | 14,85801 | 10,49567 |
| | Prob. | 0,00000 | 0,00000 | 0,00000 | 0,00000 | 0,00000 | 0,00000 | 0,00000 |

**Table 3:** DCC-GARCH model estimates

| | CAC | | DAX | | FTSE | | IBEX | | ISEQ | | PSI | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $\alpha$ | $\beta$ | $\alpha$ | $\beta$ | $\alpha$ | $\beta$ | $\alpha$ | $\beta$ | $\alpha$ | $\beta$ | $\alpha$ | $\beta$ |
| ATG | 0,022 (0,000) | 0,971 (0,000) | 0,021 (0,000) | 0,973 (0,000) | 0,026 (0,000) | 0,965 (0,000) | 0,019 (0,000) | 0,977 (0,000) | 0,027 (0,000) | 0,956 (0,000) | 0,019 (0,000) | 0,973 (0,000) |
| CAC | | | 0,033 (0,000) | 0,965 (0,000) | 0,059 (0,000) | 0,929 (0,000) | 0,034 (0,000) | 0,953 (0,000) | 0,036 (0,000) | 0,951 (0,000) | 0,030 (0,000) | 0,953 (0,000) |
| DAX | | | | | 0,047 (0,000) | 0,942 (0,000) | 0,044 (0,000) | 0,943 (0,000) | 0,032 (0,000) | 0,959 (0,000) | 0,018 (0,000) | 0,974 (0,000) |
| FTSE | | | | | | | 0,040 (0,000) | 0,950 (0,000) | 0,023 (0,000) | 0,965 (0,000) | 0,019 (0,000) | 0,974 (0,000) |
| IBEX | | | | | | | | | 0,028 (0,000) | 0,959 (0,000) | 0,038 (0,000) | 0,942 (0,000) |
| ISEQ | | | | | | | | | | | 0,033 (0,000) | 0,945 (0,000) |

Note: values between parentheses show probability values.

**Table 5:** Testing the effect of contagion between the Global Financial Crisis sub-period and the Dot-Com sub-period (observed values for t)

| | CAC | DAX | FTSE | IBEX | ISEQ | PSI |
|---|---|---|---|---|---|---|
| ATG | 34,098 (0,000) | 31,747 (0,000) | 27,046 (0,000) | 47,617 (0,000) | 26,176 (0,000) | 35,449 (0,000) |
| CAC | | 48,225 (0,000) | 32,114 (0,000) | 19,522 (0,000) | 36,079 (0,000) | 19,201 (0,000) |
| DAX | | | 43,269 (0,000) | 22,447 (0,000) | 44,397 (0,000) | 27,133 (0,000) |
| FTSE | | | | 23,765 (0,000) | 33,765 (0,000) | 32,271 (0,000) |
| IBEX | | | | | 34,246 (0,000) | 18,647 (0,000) |
| ISEQ | | | | | | 31,024 (0,000) |

Note: values between parentheses show probability values, rejecting H0 if p-value<0.05.