Analysis of contagion from the constant conditional correlation model with Markov regime switching

Pedro Nielsen Rotta
Pedro Luiz Valls Pereira
Analysis of Contagion from the Constant Conditional Correlation Model with Markov Regime Switching

Pedro Nielsen Rotta (EESP-FGV) and Pedro L. Valls Pereira (EESP-FGV and CEQEF-FGV)

18th January 2013

Abstract

Over the last decades, the analysis of the transmissions of international financial events has become the subject of many academic studies focused on multivariate volatility models volatility. The goal of this study is to evaluate the financial contagion between stock market returns. The econometric approach employed was originally presented by Pelletier (2006), named Regime Switching Dynamic Correlation (RSDC). This methodology involves the combination of Constant Conditional Correlation Model (CCC) proposed by Bollerslev (1990) with Markov Regime Switching Model suggested by Hamilton and Susmel (1994). A modification was made in the original RSDC model, the introduction of the GJR-GARCH model formulated in Glosten, Jagannathan e Runkle (1993), on the equation of the conditional univariate variances to allow asymmetric effects in volatility be captured. The database was built with the series of daily closing stock market indices in the United States (SP500), United Kingdom (FTSE100), Brazil (IBOVESP A) and South Korea (KOSPI) for the period from 02/01/2003 to 09/20/2012. Throughout the work the methodology was compared with others most widespread in the literature, and the model RSDC with two regimes was defined as the most appropriate for the selected sample. The set of results provide evidence for the existence of financial contagion between markets of the four countries considering the definition of financial contagion from the World Bank called very restrictive. Such a conclusion should be evaluated carefully considering the wide diversity of definitions of contagion in the literature.
1 Introduction

Globalization, deregulation and technological advances have deeply changed the relation between financial markets of different countries. There is sufficient evidence supporting that the increase of velocity of information transmission was partially responsible to induce stronger stock market integration. On closer inspection, there were questions about what would be the disadvantages of this process. Among the many negative aspects pointed out, one of them relates to the intensification of the financial contagion phenomenon and the losses linked to discontinuities in the mechanisms of shocks propagation. The closer relationship between markets can lead to an extremely important increase in vulnerability of economies when facing external financial shocks. Thus, financial contagion raises essential issues both for economic policy makers and international investors seeking to diversify risks. During the last two decades, the analysis of patterns of international spread of financial events became the subject of many academic studies, specially empirical research focused on volatility models.

In this context, the goal of this study is to evaluate the financial contagion between stock market returns. The econometric approach employed was originally presented by Pelletier (2006), named Regime Switching Dynamic Correlation (RSDC), which involves the combination of Constant Conditional Correlation Model (CCC) proposed by Bollerslev (1990) with Markov Regime Switching Model suggested by Hamilton and Susmel (1994). A modification was made in the original model RSDC: the introduction of the GJR-GARCH Glosten model, formulated in Glosten, Jagannathan e Runkle (1993), on the equation of the conditional univariate variances to allow asymmetric effects in volatility be captured. It is worth noting that is not part of the scope of this work to identify possible causes or predict the economic consequences of the financial contagion.

The RSDC model structure incorporates decomposition of covariance matrices into standard deviations and correlations. The correlation matrix follows a regime switching model and, therefore, stays constant within a regime, but different across the regimes. Transitions between these regimes are governed by a Markov chain. The central concept in this type of model is to decompose a series in a finite sequence of stochastic processes, that is, divide the series in regimes. Considering this characteristic, this model can be defined as piecewise linear since the process is linear in each regime, however with a non-linear structure when considering the entire procedure.

Besides the features described above, there are two main arguments for choosing the RSDC model as an alternative to DCC. The first concerns the absence of the need to define a priori which are the periods of financial crises, because the RSDC model incorporates regime changes to its dynamics. This procedure is made endogenously, since the latent Markov state variable determines which regime prevails at each instant of time. The second is the idea that (probably) the contribution to the literature could be higher, given that the
DCC is already very widespread and used for contagion tests performed in the last ten years. To complement the analysis of this work, a comparison between the results of both models is presented in Chapter 5.

The database was built with the series of daily closing stock market indices in the United States (SP500), United Kingdom (FTSE100), Brazil (IBOVESP A) and South Korea (KOSPI) for the period from 02/01/2003 to 09/20/2012. The reason for choosing this group of countries was the idea of having two representatives from different regions of developed markets (Europe and North America) and two from emerging markets (South America, and Asia).

The rest of the paper is organized as follows. Chapter 2 provides literature review on definitions of contagion and econometric approaches. Chapter 3 outlines the econometric methodology employed. The Chapters 4 and 5 describe, respectively, the database and the main results. Finally, Chapter 6 summarizes the main conclusions of this work.

2 Literature Review

2.1 Contagion Definition

In the last two decades, the analysis of the traditional pattern of international spread of financial events became a target of academic production focused on modeling volatility. Almost all of these works are faced with a primary difficult, the absence of a common definition of financial contagion.

The evidence of heterogeneity of definitions can be illustrated by the work of Pericoli and Sbracia (2001) that suggested five different definitions of contagion: significantly increase in the probability of a crisis in a country conditional on the existence of a crisis in another country; overflow (spillover) of volatility of a country in crisis for the financial markets of other countries; strong growth of co-movements of prices and quantities across markets, conditional on a crisis in one market or group of markets; changes in the transmission channel of shocks across markets; excess of co-movements not explained by economic fundamentals.

A substantial part of the academic contagion research discusses the distinction between interdependence and contagion. This extensive literature has been reviewed by Dornbusch, Park and Claessens (2000), Dungey, Fry and Martin (2005), Pesaran and Pick (2007) and Marcal et al (2011). Masson (1998) came up with a three category classification. The first class, called monsoonal effects, suggests that financial crises seem to be contagious because of the correlation between macroeconomic variables of the country. Second, financial crises can be transmitted between countries through overflow (spillover): a crisis affects another country through external links, such as trading. These first two categories illustrate situations of interdependence. Finally, the third
category, referring to the theory of pure contagion defines that a crisis in one country can cause a crisis in another country without affecting the economic fundamentals between them.

The World Bank \footnote{Available at World Bank site: http://worldbank.org. Direct link to the definitions http://go.worldbank.org/JIBDRK3YC0} offers three different definitions of contagion: broad, restrictive and very restrictive. In the broad definition, the contagion is the cross-country transmission of shocks or the general cross-country spillover effects. Contagion can take place both during good times and bad times. Then, contagion does not need to be related to crises. By the restrictive definition, contagion is the transmission of shocks to other countries or the cross-country correlation, beyond any fundamental link among the countries and beyond common shocks. This definition is usually referred as excess co-movement, commonly explained by herding behavior. The very restrictive definition says that contagion occurs when cross-country correlations increase during crisis times relative to correlations during tranquil times. This last definition can be interpreted as the breakdown in the transmission mechanism that occurs during a period of turbulence, also commonly called shift-contagion.

After reviewing the literature described, the definition of contagion adopted will be the same as Forbes and Rigobon (2002). This definition is the same as that called very restrictive by the World Bank. Thus, we can define contagion as a shift in the pattern of correlation between the returns of the stock market indices of different countries when comparing periods of calm and periods of financial crises.

Whereas that in econometric methodology, to be presented in Chapter 3, is not used any macroeconomic variable or economic fundamentals, is being undertaken in some way as a premise, that these factors or mechanisms would not be able to transmit the effects of crises observed from 2003 until 2012 so quickly and abruptly. In Chapter 6 (Conclusion) a reference is made to this question, which is directly related to the distinction between the definition of interdependence and contagion, as a suggestion for future extension of this study.

2.2 Econometric Approaches

Likewise there is no uniformity in the definition of financial contagion, there is no consensus in the literature about the econometric methodology to be employed. Among the major works on the subject, it is possible to highlight the work of Forbes and Rigobon (2002) who applied a Vector Autoregressive Model (VAR) and a measure of adjusted correlation for the detection of contagion during the crises in Mexico in 1994 and Asia in 1997 based on data of 29 countries. Using the same database, Corsetti et al (2005) presented a critical review of the adjusted correlation measure and applied a standard factor model for returns that do not impose any restrictions on the variance of the
common factors. With respect to factor models, the approach of Lopes and Migon (2002) consisted of traditional techniques of factor models combined with stochastic volatility models to study the dependence between the indices of stock prices in Latin America and North America. The work of Dungey et al (2004) provides a detailed review of methodologies that are based on very close definitions of contagion so it was possible to build a homogeneous framework to highlight the main similarities and differences between the various approaches.

Gradually, methodologies converged for conditional heteroscedasticity models, after the seminal work of Engle (1982) and Bollerslev (1986). Such models were, in short time, generalized to multivariate versions for two main formulations. The VEC model in which Bollerslev, Engle and Wooldridge (1988) extended the GARCH-M model for multivariate context using the operator VECH. And the other formulation was the BEKK model developed by Engle and Kroner (1995). The name BEKK refers to the initials of each of the authors Baba, Engle, Kraft and Kroner.

The multivariate GARCH models have attracted considerable interest because of its direct application both in economic and finance empirical research. Nevertheless, the first order of obstacles arose when considered large dimension specifications due to the complexity of computational procedures to estimate parameters resulting from the high number of coefficients. Such difficulties encouraged many academic studies to submit enhancements and alternatives to traditional multivariate GARCH models.

One of the most widespread models of multivariate volatility model is certainly the Constant Conditional Correlation (CCC) of Bollerslev (1990), in which the covariance of a vector of returns are decomposed into variances and correlations. The main assumption in this model is that the conditional correlations are constant over time. The advantage is that the CCC was designed to have the flexibility of a univariate GARCH but not the complexity of a traditional multivariate GARCH. Engle (2002) and Tse and Tsui (2002) presented an extension to the CCC model that uses the same decomposition of the covariance matrix, but instead of assuming constant correlation, the authors propose a GARCH dynamic for correlation matrices. Such models, named Dynamic Conditional Correlation (DCC) have numerical stability even for large dimension problems because, as well as the CCC, estimation procedure may be done in two stages. The main benefit of the correlations models over the BEKK and VEC specifications is the parsimony in parameterization, which allows to overcome the barriers to implement models in dimensions larger than the bivariate one. Among the studies that used these multivariate volatility models for investigation of contagion: Lombardi et al (2004), Marcal and Valls Pereira (2008) and Filleti, Hotta and Zevallos (2008).

The combination of multivariate volatility models with regime switching models is a relatively recent approach. Denis Pelletier (2006) developed the Regime Switching Dynamic Correlation (RSDC) model which served as the basis for the methodology of the present article. The RSDC allows the unconditional correlation to be conducted by an unobservable component character-
ized by the Markov chain. An extension of the RSDC model was presented in Billio and Caporin (2005). This study elaborates a more general framework building the regime switching upon the DCC (MS-DCC), which enables for time-varying correlation within each correlation regime. The authors provide an empirical analysis of the phenomenon of contagion by comparing the results with traditional representations like CCC and DCC.

Finally, it is worth mentioning the work of Chen (2009) that also applies the RSDC model proposed by Pelletier (2006) for the series of USA stocks and bonds between 1998 and 2000. The author points out that a DCC structure instead of CCC in a GARCH model with Markov regime switch would hugely complicate the already complicated estimation process. The amount of observations in each regime would not be enough to achieve a robust estimation of DCC. In Idier (2009) is also made reference to the fact that adding more than 10 extra parameters would not likely produce a great improvement and, thus, this formulation (MS-DCC) was not chosen as the central conductor of this study. Therefore, the model RSDC (or MS-CCC) would be sufficient to capture the dependency on the correlation.

3 Methodology

3.1 RSDC Model

The methodology of this study was based on the Regime Switching Dynamic Correlation (RSDC) model proposed by Pelletier (2006). It is the combination of Constant Conditional Correlation (CCC) model presented by Bollerslev (1990) with Markov Regime Switching suggested by Hamilton and Susmel (1994). We made a modification in the original RSDC, introducing the GJR-GARCH² on the equation of the conditional univariate variances to allow asymmetric effects in volatility be captured. The GJR-GARCH model was formulated by Glosten, runkle and Jagannathan (1993).

In the CCC model of Bollerslev (1990), conditional covariance are parameterized to be proportional to the product of the corresponding standard deviations. The covariance of a vector of returns are decomposed into standard deviations and correlations. Thus, both the computational processing required for estimation was reduced and the imposition of conditions to ensure the covariance matrix is positive semi-definite become simpler. Nevertheless, a major

²In Pelletier (2006), the model for the volatility of univariate time series was the ARMACH specification proposed by Taylor (1986). The author's argument was that by using a model such as GARCH for the variance, the covariance becomes the product of a correlation and the square-root of the product of two variances and this square-root introduces non-linearities that will prohibit analytic computation of conditional expectations.
assumption of the model is that the conditional correlations are constant over time and this supposition is not always supported by data according to Engle and Sheppard (2001).

Given this constraint, Pelletier (2006) proposed a new multivariate volatility model (RSDC). The structure of this model also incorporates the decomposition of covariance matrices into standard deviations and correlations, but the correlations have some dynamism. The correlation matrix follows a regime switching model and, therefore, stays constant within a regime, but different across the regimes. Transitions between these regimes are governed by a Markov chain. The CCC model can be considered a special case of RSDC, where the number of regimes is equal to 1.

An alternative approach to the one chosen in this study could be the Dynamic Conditional Correlation (DCC) model formulated by Engle (2002) Tse and Tsui (2002), that uses the same decomposition of the covariance matrix of Bollerslev (1990), but instead of assuming constant correlation, the authors propose that these are characterized according to a GARCH type dynamic. According to Pelletier (2006), it is reasonable to question whether a GARCH type approach for correlations would be more appropriate because the dynamic of the correlation may be inherently different from the behavior of a covariance. For instance, the correlation have upper and lower limits while the covariance does not. Another issue is the high persistence of the GARCH models. Diebold (1986) evaluates that this high persistence may be caused by the failure to observe changes of the unconditional volatility. In Chapter 5 (Results) there is an exercise performed with dummies to offer evidence on the issue of persistence.

In addition to the points raised, as also stated in the introduction, there are two fundamental aspects to choose the RSDC Model instead of DCC. The first concerns the absence of the need to define a priori which are the periods of financial crises, because the RSDC model incorporates regime changes to its dynamics. This procedure is made endogenously, since the latent Markov state variable determines which regime prevails at each instant of time. The second is the idea that (probably) the contribution to the literature could be higher, given that the DCC is already very widespread and used for contagion tests performed in the last ten years. To complement the analysis of this work, a comparison between the results of both models is presented in Chapter 5.

Following the methodology presented in Pelletier (2006), a filtered process $Y_t$ with K variables can be represented as follows:

$$Y_t = H_t^{1/2}U_t$$

(1)

with $U_t$ an independent and identically distributed process $(0, I_k)$. The time-varying covariance matrix $H_t$ can be decomposed into:

$$H_t = S_t \Gamma_t S_t$$

(2)
with $S_t$ a diagonal matrix composed of the standard deviations $s_{mt}$ with $m=1,\ldots,k$ and $\Gamma_t$ a correlation matrix.

$$S_t = \begin{pmatrix} s_{1t} & 0 & 0 & \cdots & 0 \\ 0 & s_{2t} & 0 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & \cdots & 0 & \cdots & 0 \\ 0 & \cdots & 0 & 0 & s_{kt} \end{pmatrix} \quad (3)$$

Each variance $s^2_{mt}$ is modeled by a univariate GARCH. In the present study, unlike Pelletier, we will use the GJR-GARCH model to capture the negative skewness, as follows:

$$s^2_{mt} = \omega + \sum_{i=1}^{q} \alpha_{i} \epsilon_{t-i}^{2} + \sum_{z=1}^{q} \gamma_{z} \epsilon_{t-z}^{2} I(\epsilon_{t-z}) + \sum_{j=1}^{p} \beta_{j} s_{t-j}^{2} \quad (4)$$

$$I(\epsilon_{t-z}) = \begin{cases} 1, & \text{se } \epsilon_{t-z} < 0 \\ 0, & \text{caso contrário} \end{cases} \quad (5)$$

The introduction of the Markov regime dynamics is made in the correlation matrix. Therefore, $\Gamma_t$ takes the following form:

$$\Gamma_n = \begin{pmatrix} 1 & \rho_{12} & \rho_{13} & \cdots & \rho_{1k} \\ \rho_{21} & 1 & \rho_{23} & \cdots & \rho_{2k} \\ \rho_{31} & \rho_{32} & \ddots & \cdots & \vdots \\ \vdots & \vdots & \ddots & \ddots & \vdots \\ \rho_{k1} & \rho_{k2} & \cdots & \rho_{kk-1} & 1 \end{pmatrix} \quad (6)$$

$$\Gamma_t = \sum_{n=1}^{N} I(\Delta_t=n) \Gamma_n \quad (7)$$

where $\Delta_t$ is a random variable independent from $U_t$ which is defined as a state variable. This state variable follows a first order Markov process and can take only integer values $\{1,\ldots,N\}$. This representation of $\Gamma_t$ shows another advantage of the RSDC model. At the estimation stage, the correlation matrix $\Gamma_t$, may have only N different configurations and hence need to be reversed only N times while in the DCC model the correlation matrix has to be inverted to each observation. When working with a larger number of series, this can be a valuable advantage in terms of computational implementation.
The probability of $\Delta_t$ be equal to $j$ is given only as a function of $\Delta_{t-1}$:

$$P(\Delta_t = j | \Delta_{t-1} = i) = p_{ij} \quad (8)$$

With the constraint:

$$p_{i1} + p_{i2} + \ldots + p_{iN} = 1 \quad (9)$$

The probabilities associated with each system can be represented by a matrix ($N \times N$) usually known as the transition matrix:

$$\Pi = \begin{pmatrix} p_{11} & p_{12} & \ldots & p_{1N} \\ p_{21} & p_{22} & \ldots & p_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ p_{N1} & p_{N2} & \ldots & p_{NN} \end{pmatrix} \quad (10)$$

The regime switching model allows to calculate the expected duration $D$ in each regime. This is the average length of each regime conditioned on the information of being in a specific regime. The final formula of $E(D)$ can be obtained by:

$$E(D) = \sum_{j=1}^{\infty} j P[D = j] =$$

$$D = 1, \text{se } \Delta_t = j \text{ e } \Delta \neq j; \quad P[D = 1] = (1 - p_{jj})$$

$$D = 2, \text{se } \Delta_t = \Delta_{t+1} = j \text{ e } \Delta \neq j; \quad P[D = 2] = p_{jj} (1 - p_{jj})$$

$$D = 3, \text{se } \Delta_t = \Delta_{t+1} = \Delta_{t+2} = j \text{ e } \Delta_{t+3} \neq j; \quad P[D = 3] = p_{jj}^2 (1 - p_{jj})$$

$$E(D) = (1 - p_{jj}) + 2p_{jj} (1 - p_{jj}) + 3p_{jj}^2 (1 - p_{jj}) + \ldots$$

$$E(D) = \frac{1}{(1 - p_{jj})} \quad (11)$$
Another rich information that can be extracted from the model is the ergodic probability of each regime. The probabilities associated with each state in equilibrium. It can be done as follows:

\[ \pi = \Pi \pi \]

\[
\begin{pmatrix}
\pi_1 \\
\pi_2 \\
\vdots \\
\pi_k
\end{pmatrix}
\begin{pmatrix}
\pi_1 \\
\pi_2 \\
\vdots \\
\pi_k
\end{pmatrix}
= \Pi
\begin{pmatrix}
\pi_1 \\
\pi_2 \\
\vdots \\
\pi_k
\end{pmatrix}
\]

(12)

\[
\sum_{i=1}^{n} \pi_i = 1
\]

(13)

\[ \pi_i \geq 0 \]

### 3.2 Estimation

According to Pelletier (2006), the estimation of the RSDC model can, in theory, be done in one step by calculating the following expression to maximize the likelihood:

\[
QL(\theta; Y) = \sum_{t=1}^{T} \log f(Y_t | Y_{t-1})
\]

(14)

where \( Y_{t-1} = \{Y_{t-1}, Y_{t-2}, \ldots \} \) and \( \theta \) is the vector of parameters. The computation of (14) is done using the Hamilton’s filter presented in Hamilton (1989), because the state variable \( \Delta_t \) is an unobserved component. However, when working with more than a few series the one-step procedure becomes very complex due to the high number of parameters to be estimated. Therefore, in the present study will only be applied the two-steps estimation procedure.

The total space of parameters \( \theta \) can be separated in space \( \theta_1 \), referring to the parameters of the univariate volatility models for marginal distributions,
and $\theta_2$, for the parameters in the correlation model. Denoting $QL_1$ the likelihood of parameter space $\theta_1$ and $QL_2$ the likelihood of parameter space $\theta_2$, we have:

$$QL_1 (\theta_1; Y) = -\frac{1}{2} \sum_{t=1}^{T} \left( K \log(2\pi) + 2 \log(|S_t|) + U_t' U_t \right)$$ (15)

$$QL_2 (\theta_2; Y, \theta_1) = -\frac{1}{2} \sum_{t=1}^{T} \left( K \log(2\pi) + 2 \log(|\Gamma_t|) + U_t' \Gamma_t^{-1} U_t \right)$$ (16)

The likelihood $QL_1$ has two important features. First, it is the sum of $K$ univariate log-likelihoods and, therefore, equivalent to maximizing each univariate log-likelihood separately. Second, the calculation of each log-likelihood is simple, since it does not involve the use of filter Hamilton.

Maximizing $QL_2$, unlike $QL_1$, requires the application of the Hamilton’s filter, as the state variable $\Delta_t$ is an unobserved component as mentioned before. Since the number of parameters in the correlation model grows quadratically with the amount of series involved, the direct maximization of $QL_2$ when $\Gamma_t$ has a high dimension may not be simple. To solve this problem, it is possible to use EM algorithm (Expectation Maximization). According to Santos et al (2006), this algorithm aims to generate new models from an initial one through iteration. This iterative process should obey a stop criterion. The EM algorithm was not developed specifically for Markov models but to general problems of statistical inference to find the value of a parameter that maximizes the likelihood function.
4 Dataset

4.1 Description

The database construction involved the collection\textsuperscript{3} of daily closing stock markets indices of the United States (SP500), UK (FTSE 100), Brazil (Bovespa Index) and South Korea (KOSPI) from the period 02/01/2003 to 09/20/2012. The reason for choosing this group of countries was the idea of having two representatives from different regions of developed markets (North America and Europe) and two from emerging markets (South America and Asia).

![Graphs of stock market indices SP500, IBOV, FTSE100, and KOSPI from 2003 to 2012.]

Regarding the sample definition, the intention was to select an extensive set of historical data with approximately a 10 year period, which amounted to 2536 observations for each series, and is characterized by the presence of financial crisis events. On this point, we can mention mainly the Subprime crises of 2008 and debt crisis in Europe worsened in 2011. However, as previously mentioned, it is not necessary to define a priori the moments of higher volatility generated by financial crises. The Markov Regime Switch Model is able to determine endogenously such periods. The stock market indices graphs illustrate the behavior of each series and reveals a greater range of values for the second

\textsuperscript{3}Data obtained by Reuters Ecowin system from the following codes: usa15510 (sp500) / brc15500 (ibov) / gbr15500 (ftse100) / krw15500 (kosp)
half of the sample. Furthermore, a preliminary visual analysis shows a joint decrease of all series during the crisis mentioned above.

4.2 Initial Analysis

Before the estimation stage, the initial database suffered some treatments. The first was to estimate a Local Level model for each series in order to impute an estimate for missing values (missing data) related to the days when there was no negotiation\(^4\). The missing values were replaced by the smoothed estimates of the component level. This procedure was done with the software package OxMetrics STAMP 8.2 as suggested by Koopman et al (2009).

The second data treatment was the construction of the return series by taking 100 times the first difference of the natural logarithm of each series.

![Figure 2: Stock Market Returns](image)

The third treatment involved the trading days synchronization because of time zone differences. With respect to Greenwich time (GMT), Seoul is GMT +9, and thus operationally one day ahead of negotiations in other regions of the series chosen. Following Santos and Valls Pereira (2011), data synchronization respected the following rule: \( [SP500_t, IBOV_t, FTSE_t, KOSPI_{t+1}] \).

The analysis of descriptive statistics, graphs and histograms of the returns confirm the stylized facts of financial time series. The sampling distribution

\(^4\)Number of missing data: SP500-87 / IBOVESPA-124 / FTSE100-79 / KOSPI-118
of the four returns series are characterized by heavier tails (leptokurtic) than a normal distribution, mean close to zero and volatility clustering. Also, all returns reported negative asymmetry.

4.3 Filtering

Whereas volatility models have as its premise the absence of serial correlation as mentioned previously, it was necessary to examine the validity of this hypothesis. The autocorrelations for the series of returns, despite not having high estimates statistically different from zero. In order to model the autocorrelation structure of the data, we performed a filter for the conditional mean through the estimation of ARMA \((p, q)\) models.

The determination of the order \(p\) and \(q\) of these models was based on the Akaike Information Criterion (AIC), Hannan-Quinn (HQ) and Schwarz (SC or BIC), tests on residuals and the parameters significance. With respect to residuals, both the LM test and Durbin Watson test corroborate the conclusion of no serial autocorrelation. Finally, we have calculated the statistics for the ARCH Heteroscedasticity test and the null hypothesis of no heteroskedasticity is rejected justifying the application of volatility models in this study.

Before presenting the table 1 below it is extremely important to comment about the number of observations in the sample after the database treatment and the filtering process. In treatment step, the synchronization and calculation of returns resulted in the loss of two observations. The filtering process due to the higher order of ARMA models selected, was responsible for 3 more observations losses. Thus, the final sample has 2531 observations over the period from 01/08/2003 to 09/19/2012.
<table>
<thead>
<tr>
<th>(p, q)</th>
<th>Autocorrelation*</th>
<th>Heteroscedasticity**</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>L(1) L(3) L(6) L(9)</td>
<td>L(1) L(3) L(6) L(9)</td>
</tr>
<tr>
<td>SP</td>
<td>(3, 3) 0.01 0.73 0.70 1.88 (0.91) (0.53) (0.65) (0.05)</td>
<td>2.0006 99.0 (0.00) 201.8 (0.00) 165.3 (0.00) 120.5 (0.00)</td>
</tr>
<tr>
<td>IB</td>
<td>(2, 3) 1.20 1.37 1.05 1.20 (0.27) (0.24) (0.39) (0.29)</td>
<td>1.9987 83.6 (0.00) 176.2 (0.00) 115.5 (0.00) 99.5 (0.00)</td>
</tr>
<tr>
<td>FT</td>
<td>(3, 3) 1.15 0.95 1.16 1.34 (0.28) (0.41) (0.32) (0.20)</td>
<td>2.0046 138.4 (0.00) 157.7 (0.00) 104.0 (0.00) 73.7 (0.00)</td>
</tr>
<tr>
<td>KO</td>
<td>(3, 3) 0.10 0.88 1.33 1.54 (0.75) (0.44) (0.23) (0.12)</td>
<td>2.0053 111.5 (0.00) 84.8 (0.00) 123.6 (0.00) 85.0 (0.00)</td>
</tr>
</tbody>
</table>

*F Estatistic and Prob of LM Serial Autocorrelation Test

**F Estatistic and Prob of ARCH Heteroscedasticity Test

Table 1: Residual Tests

5 Results

5.1 RSDC Model

5.1.1 Marginal Distribution

After performing the filtering for the conditional mean of the series through the estimation of the ARMA (p, q) models presented in section 4.3, were estimated GJR-GARCH models for the univariate variance equation of each series. As mentioned above, the introduction of GJR-GARCH model at this stage consists of a modification on the original RSDC developed by Pelletier (2006). The purpose of this change was to allow capture the asymmetric effects more adequately. The coefficient estimates and standard errors are reported in Table 3 as well as the persistence $\lambda$ and the half-life (MV) of the series computed according to the formulas below. The term $\gamma$ is the coefficient of skewness specified in equations 4 and 5.

$$\lambda = \alpha + \beta + \frac{\gamma}{2}$$  \hspace{1cm} (17)

$$MV = 1 - \left( \frac{\log[2]}{\log[\lambda]} \right)$$  \hspace{1cm} (18)

5There are other type of GARCH models capable to capture skewness such as EGARCH proposed by Nelson (1991), TGARCH formulated by Zakoian (1994) and QGARCH of Sentana (1995) among other models.
The graph of the estimated conditional variances in this first stage can be viewed below.

The GJR-GARCH (1,1) models estimates reveals, one of the results often found in the empirical finance literature, that is a high persistence and high half-life, as can be seen by the values on Table 2. According to Diebold (1986), this high persistence may be associated with no observation of changes in

<table>
<thead>
<tr>
<th></th>
<th>$\omega$</th>
<th>$\alpha$</th>
<th>$\gamma$</th>
<th>$\beta$</th>
<th>$\lambda$</th>
<th>$MV$</th>
</tr>
</thead>
<tbody>
<tr>
<td>SP500</td>
<td>0.0143</td>
<td>-0.0130</td>
<td>0.1381</td>
<td>0.9296</td>
<td>0.986</td>
<td>49</td>
</tr>
<tr>
<td></td>
<td>(0.0017)</td>
<td>(0.0064)</td>
<td>(0.0113)</td>
<td>(0.0075)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>IBOV</td>
<td>0.1061</td>
<td>0.0055</td>
<td>0.1301</td>
<td>0.8924</td>
<td>0.963</td>
<td>19</td>
</tr>
<tr>
<td></td>
<td>(0.0155)</td>
<td>(0.0095)</td>
<td>(0.0162)</td>
<td>(0.0121)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>FTSE100</td>
<td>0.0152</td>
<td>0.0000</td>
<td>0.1584</td>
<td>0.9086</td>
<td>0.988</td>
<td>58</td>
</tr>
<tr>
<td></td>
<td>(0.0023)</td>
<td>(0.0092)</td>
<td>(0.0138)</td>
<td>(0.0090)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>KOSPI</td>
<td>0.0617</td>
<td>-0.0131</td>
<td>0.1791</td>
<td>0.8897</td>
<td>0.966</td>
<td>21</td>
</tr>
<tr>
<td></td>
<td>(0.0068)</td>
<td>(0.0078)</td>
<td>(0.0166)</td>
<td>(0.0091)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 2: Univariate GJR-GARCH (1,1)
the unconditional volatility over time. The relevance of this point is that
the change in unconditional volatility would be an evidence of changes in the
unconditional correlation between the series over the sample, which justifies
the application of the regime switching model to be discussed later.

The same way as in Almeida and Valls Pereira (1999), was created an ad
hoc dummy \( d_1 \) with value 1 for the period from Jan/2008 to Jun/2009 and 0 for
the rest, based only on visual inspection. The idea was just to show that the
inclusion of an intercept dummy in the equation of univariate variances would
be capable of changing the persistence and the half-life of the series providing,
in this way, further evidence of change in the unconditional volatility over
time. With this objective, the regressions were recalculated for the marginal
distributions, but this time incorporating the dummy in each equation. The
results in Table 4, shows a reduction of persistence and half-life for the four
series. On average, the persistence decrease from 0.98 to 0.96 and from 37 to 25
days in half-life. Moreover, in all cases the dummy was statistically significant.

Returning to equation 4, the GJR-GARCH (1,1) model specification with
dummy and \( q, n \) and \( p \) equal to 1 followed:

\[
\sigma^2_{mt} = \omega_0 + \omega_1 d_1 + \sum_{i=1}^{q} \alpha_i \epsilon^2_{t-i} + \sum_{z=1}^{n} \gamma_z \epsilon^2_{t-z} I(\epsilon_{t-z}) + \sum_{j=1}^{p} \beta_j \sigma^2_{t-j}
\]  

(19)

<table>
<thead>
<tr>
<th></th>
<th>( \omega )</th>
<th>( d_1 )</th>
<th>( \alpha )</th>
<th>( \gamma )</th>
<th>( \beta )</th>
<th>( \lambda )</th>
<th>( MV )</th>
</tr>
</thead>
<tbody>
<tr>
<td>SP500</td>
<td>0.0168</td>
<td>0.0338</td>
<td>-0.0130</td>
<td>0.1395</td>
<td>0.9237</td>
<td>0.980</td>
<td>36</td>
</tr>
<tr>
<td></td>
<td>(0.0020)</td>
<td>(0.0142)</td>
<td>(0.0063)</td>
<td>(0.0119)</td>
<td>(0.0085)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>IBOV</td>
<td>0.1438</td>
<td>0.1664</td>
<td>-0.0050</td>
<td>0.1466</td>
<td>0.8727</td>
<td>0.941</td>
<td>12</td>
</tr>
<tr>
<td></td>
<td>(0.0210)</td>
<td>(0.0511)</td>
<td>(0.0098)</td>
<td>(0.0190)</td>
<td>(0.0154)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>FTSE100</td>
<td>0.0211</td>
<td>0.0600</td>
<td>-0.0051</td>
<td>0.1832</td>
<td>0.8915</td>
<td>0.978</td>
<td>32</td>
</tr>
<tr>
<td></td>
<td>(0.0032)</td>
<td>(0.0178)</td>
<td>(0.0106)</td>
<td>(0.0181)</td>
<td>(0.0119)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>KOSPI</td>
<td>0.0684</td>
<td>0.0423</td>
<td>-0.0151</td>
<td>0.1849</td>
<td>0.8819</td>
<td>0.959</td>
<td>18</td>
</tr>
<tr>
<td></td>
<td>(0.0079)</td>
<td>(0.0198)</td>
<td>(0.0078)</td>
<td>(0.0175)</td>
<td>(0.0104)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 3: Univariate GJR-GARCH (1,1) with Dummies
5.1.2 2 Regimes

After the end of marginal distributions modeling stage, we estimate the correlation matrices with the assumption of the presence of only two regimes. In the next section we estimate the correlation matrices with the assumption of the presence of three regimes. The regime identified as state 1 is defined as the high volatility (turbulence) one and the regime referred to as state 2 is characterized by low volatility (calm). The transition probability matrix $\Pi$ indicates that the regimes are persistent because the probability of being in state 1 at time $t+1$ conditional on being at that same state at time $t$ is 0.99 and the similar statistic for the second state is 0.98. Returning to section 2 (Methodology), these values are given, respectively, by the probabilities $p_{11}$ and $p_{22}$ defined by equation 8. Using the derivation of equation 12, the higher persistence of state 1 reflects a greater average expected duration $E(D)$ of this regime which is 147 days versus 75 days of state 2. With respect to the number of observations in each regime, the state 1 has also a greater number of 1646 points against 885 on the other regime. From the ergodic probabilities of each regime calculated from equation 12, it can be observed that the probability of state 1 is 0.66 and higher than of the State 2 (0.34).

<table>
<thead>
<tr>
<th>$\Pi$</th>
<th>$\Delta_t = 1$</th>
<th>$\Delta_t = 2$</th>
<th>$\Delta_t = 1$</th>
<th>$\Delta_t = 2$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.993</td>
<td>0.007</td>
<td>1646</td>
<td>885</td>
</tr>
<tr>
<td></td>
<td>(0.004)</td>
<td>(0.008)</td>
<td>0.66</td>
<td>0.34</td>
</tr>
<tr>
<td></td>
<td>0.987</td>
<td></td>
<td>147</td>
<td>75</td>
</tr>
</tbody>
</table>

Table 4: Transition Matrix with 2 Regimes

The correlation matrices defined in equations 6 and 7, reported in Table 6 provide some evidence of financial contagion according to the definition adopted in this study. The matrix $\Gamma_1$, associated with the high volatility state, presents significantly higher correlation coefficients than $\Gamma_2$ related to calm periods. As an example, the pair SP500 and Bovespa Index have a correlation coefficient of 0.47 in the calm regime and 0.75 during the turbulence state. It is essential to note that the estimates standard errors of the correlation coefficients between the pair FTSE100 and KOSPI are high and, therefore, it is not possible to assert that there is strong evidence of contagion, although statistically significant.
The analysis of the smoothed probabilities graphs reveals that these do not move very often between the regimes exhibiting relative stability and there is low uncertainty to determine which regime prevails at each instant of time, given that the probabilities are concentrated around 0 or 1 at each observation. This conclusion shows that the transition between regimes occurs not gradually but abruptly.

Another interesting aspect is the changing on the regime dominance pattern throughout the sample. During the years 2003 to mid-2007 it is possible to observe a dominance of the regime categorized as calm (state 1). These long periods of low volatility are interrupted by some points of turbulence. One possible interpretation is that a turbulence shock in a country is transmited to other markets, but when the intensity and direction are recognized, the correlation level fall like a temporary financial shock. In contrast, for the period from mid-2007 until 2012, the higher volatility state prevails in almost all observations and suggests that the financial crises events entailed permanent changes. In summary, the average duration of high volatility periods is greater in the second half of the sample.

<table>
<thead>
<tr>
<th></th>
<th>SP</th>
<th>IB</th>
<th>FT</th>
<th>KO</th>
</tr>
</thead>
<tbody>
<tr>
<td>SP</td>
<td>1.000</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>IB</td>
<td>0.754 (0.049)</td>
<td>1.000</td>
<td></td>
<td></td>
</tr>
<tr>
<td>FT</td>
<td>0.644 (0.061)</td>
<td>0.589 (0.045)</td>
<td>1.000</td>
<td></td>
</tr>
<tr>
<td>KO</td>
<td>0.448 (0.051)</td>
<td>0.433 (0.058)</td>
<td>0.346 (0.086)</td>
<td>1.000</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>SP</th>
<th>IB</th>
<th>FT</th>
<th>KO</th>
</tr>
</thead>
<tbody>
<tr>
<td>SP</td>
<td>1.000</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>IB</td>
<td>0.473 (0.043)</td>
<td>1.000</td>
<td></td>
<td></td>
</tr>
<tr>
<td>FT</td>
<td>0.403 (0.034)</td>
<td>0.294 (0.055)</td>
<td>1.000</td>
<td></td>
</tr>
<tr>
<td>KO</td>
<td>0.302 (0.022)</td>
<td>0.226 (0.034)</td>
<td>0.228 (0.027)</td>
<td>1.000</td>
</tr>
</tbody>
</table>

Table 5: Correlation Matrices for 2 Regimes
5.1.3 3 Regimes

This section will present the results for the correlation matrices with the assumption of the presence of three regimes. As will be detailed, the model with 3 regimes showed greater instability and uncertainty about the definition of the regime prevailing in each point in time. In addition, estimates standard errors increased and did not result in the same strong conclusions of the case with only two regimes. Given this context, the final conclusions of this work will be based, in most part, on the results of the model with two regimes. This will be discussed in the next section.

The regime identified as state 1 is defined as the medium volatility, the regime defined as State 2 is the high volatility regime (turbulence period) and, finally, the “State 3 is characterized by low volatility (calm period). The matrix II transition probabilities shows that the regimes of State 1, State 2 and State 3 are characterized, respectively, by low, moderate and high persistence, given that $p_{11}=0.46$, $p_{22}=0.87$ and $p_{33}=0.98$. The differences in persistence impact directly on the expected average duration $E(D)$ of each regime which is 2 days for the first state, 8 days for second state, and 48 days for the third state.
The Markov chain is spending most of its time in the turbulent regime, which has 1585 observations, versus 814 of State 3 and 132 of State 1. Regarding the ergodic probabilities for each regime, it is noted that the steady state probability of state 2 ($\pi_2 = 0.55$) is also higher than the others ($\pi_1 = 0.13$ and $\pi_3 = 0.32$).

<table>
<thead>
<tr>
<th>$\Delta_t$</th>
<th>$\Delta_t = 1$</th>
<th>$\Delta_t = 2$</th>
<th>$\Delta_t = 3$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\Pi$</td>
<td>0.462</td>
<td>0.488</td>
<td>0.050</td>
</tr>
<tr>
<td></td>
<td>(0.343)</td>
<td>(0.080)</td>
<td></td>
</tr>
<tr>
<td>$\Delta_t = 2$</td>
<td>0.128</td>
<td>0.872</td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td>(0.046)</td>
<td>(0.017)</td>
<td></td>
</tr>
<tr>
<td>$\Delta_t = 3$</td>
<td>0.008</td>
<td>0.013</td>
<td>0.979</td>
</tr>
<tr>
<td></td>
<td>(0.017)</td>
<td>(0.030)</td>
<td></td>
</tr>
</tbody>
</table>

Table 6: Transition Matrix with 3 Regimes

The correlation matrices, reported in Table 8, give some evidence of financial contagion according to the definition adopted in this study, but less incisive than in the case of 2 regimes. The matrix $\Gamma_2$, associated with the high volatility state, presents significantly higher correlation coefficients than $\Gamma_3$, related to tranquil periods. Nonetheless, the distinction between the matrix $\Gamma_1$ (medium volatility) coefficients with the other matrices is not significant for all pairs of countries. Illustrating this point, the pair SP500 and Bovespa Index, has a correlation coefficient of 0.47 during the calm regime against 0.79 in the turbulence period, and they are statistically different considering the standard errors. Nevertheless, comparing both numbers with the coefficient 0.58 (standard error 0.17) of the medium volatility regime we can not sustain the same assertion. In certain cases we can observe even an inversion. The pairs KOSPI with IBOVESPA and KOSPI with FTSE100 in matrix $\Gamma_1$ have higher coefficients than the $\Gamma_2$, what is not expected originally. A possible interpretation for these results must concern to the difficulty of defining what regime is prevailing in each time point as discussed immediately below. Before that, it is also important to note that the estimates standard errors of the correlation coefficients between the pairs are generally higher than those of the matrices with 2 regimes.
Table 7: Correlation Matrices for 3 Regimes

The analysis of the smoothed probabilities graphs allows to visualize the high uncertainty regarding the definition of the regime that is in place at each point in time, especially for the regimes of medium and high volatility. This uncertainty is related to the fact that probabilities in these regimes are not concentrated around 0 or 1 in most of the data. That argument, as previously mentioned, may help explain the results for the correlation matrices.

Another relevant aspect is that due to the lower expected average duration \( E(D) \) of State 1 and State 2, the smoothed probabilities often move between regimes. With a higher \( E(D) \), the low volatility regime does not change continuously and thus is relatively more stable. A possible explanation for these results is that the switch between the tranquil and turbulent regimes occurs abruptly as seen in section 5.1.2, and the medium volatility state would be well-defined in processes with gradual transition from low to high volatility, or vice versa, which is not the case.
5.2 Comparison with CCC and DCC models

In this section we will elaborate a comparison of the econometric approach presented so far, the RSDC model, with the Constant Conditional Correlation (CCC) model proposed by Bollerslev (1990) and the Dynamic Conditional Correlation (DCC) developed in Engle (2002). For the estimation of the CCC and DCC, we used the routines provided by Kevin Sheppard in MFE.
Toolbox for MATLAB\textsuperscript{6}. Furthermore, aiming to establish a direct and fair comparison about the RSDC relative performance, we also estimated versions of the RSDC model with the conditional variances modeled only by the standard GARCH specification. Thus, it is possible to check whether possible gains in terms of likelihood are not only linked to the introduction of the GJR model on the marginal distributions as described on section 5.1.1.

According to the analysis of the estimates reported on Table 8, there is additional evidence of the issue raised in section 5.1.1 about the high persistence of the GARCH models in general. The sum of the calculated parameters for the DCC model reveal a persistence very close to unity, as the results of the univariate GARCH estimations. It should be mentioned again that this high persistence may be associated with no observation of some change in the unconditional volatility over time.

The CCC model can be interpreted as the linear RSDC model, or when the number of regimes is equal to 1. The DCC model specification was the following:

$$\hat{\Gamma}_t = \left(1 - \sum_{i=1}^{q} a_i - \sum_{i=1}^{p} b_j\right) \Gamma + \sum_{i=1}^{q} a_i \left(\hat{U}_{t-i}\hat{U}_t\right) + \sum_{i=1}^{p} b_j \hat{\Gamma}_{t-j}$$

(20)

$$\Gamma_t = D_t^{-1}\hat{\Gamma}_t D_t^{-1}$$

(21)

The correlation matrix $\Gamma_t$ and the coefficients $a$ and $b$ from DCC model are reported below.

<table>
<thead>
<tr>
<th></th>
<th>SP</th>
<th>IB</th>
<th>FT</th>
<th>KO</th>
<th>DCC</th>
<th>a</th>
<th>b</th>
</tr>
</thead>
<tbody>
<tr>
<td>SP</td>
<td>1.0000</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>IB</td>
<td>0.6595 (0.0001)</td>
<td>1.0000</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>FT</td>
<td>0.5734 (0.0002)</td>
<td>0.4831 (0.0002)</td>
<td>1.0000</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>KO</td>
<td>0.4046 (0.0003)</td>
<td>0.3541 (0.0003)</td>
<td>0.2927 (0.0004)</td>
<td>1.0000</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 8: Results for the CCC and DCC model

\textsuperscript{6}Available in http://www.kevinshewrapid.com/wiki/MFE_Toolbox. The functions ccc_mvgarch.m and dcc_mvgarch.m were used for the CCC and DCC models, respectively.
After the estimation of the models, we created a comparative table summarizing the statistical performance of each approach in order to enrich the analysis. One of the first points to note is the increase in the likelihood from the introduction of the regime switch dynamic. As can be observed, the RSDC(2)-GJR and RSDC(3)-GJR models have -12794 points and -12753 points, respectively, while the CCC models have -14484 points and the DCC has -14407 points.

The results of RSDC(2)-GARCH and RSDC(3)-GARCH, which incorporates only the GARCH model, served to support the conclusion that the introduction of the regime switching actually entails likelihood gains. Such models even showed better performances, with respect to information criteria, than the versions that include the GJR model. However, the significant instability and uncertainty regarding the determination of the regime taking place at each instant of time was high enough for not continuing the analysis of these versions. Therefore, this study returns (in the following paragraph) the focus on the comparison between the RSDC-GJR formulation with the CCC and DCC models.

After concluding that the application of GJR RSDC model entails likelihood gains when compared with the CCC and DCC, it is necessary to establish what is the appropriate number of regimes. In other words which specification is better between RSDC (2)-GJR and RSDC (3)-GJR. A possible selection criterion would be the likelihood ratio, provided that the distribution of this test was standard. Regarding the parameters governed by the Markov chain, the test would have standard distribution if the number of regimes was kept constant according to Krolzig (1997), which is not the case. Therefore, to determine the number of regimes the test do not follow a standard distribution due to unidentified parameters under the null hypothesis.

Another alternative is to compare through information criteria. As proposed by Ryden (1995), the Schwartz information criterion may be used, since this criterion does not underestimate the minimum number of regimes. The results of Schwartz (SC), Hannan-Quinn (HQ) and Akaike (AIC) are reported on table 9. By the Schwartz information criterion the model should provide a structure with two regimes, since it has the lowest value of the statistic. By other criteria, the model RSDC(3)-GJR is preferable. It is important to remember that RSDC-GARCH models are no longer being considered.
Table 9: Models Comparison

<table>
<thead>
<tr>
<th>Model</th>
<th>MV</th>
<th>Par.</th>
<th>Obs.</th>
<th>AIC*</th>
<th>SC**</th>
<th>HQ***</th>
</tr>
</thead>
<tbody>
<tr>
<td>CCC</td>
<td>-14484</td>
<td>18</td>
<td>2531</td>
<td>11.460</td>
<td>11.501</td>
<td>11.475</td>
</tr>
<tr>
<td>DCC</td>
<td>-14407</td>
<td>20</td>
<td>2531</td>
<td>11.400</td>
<td>11.446</td>
<td>11.417</td>
</tr>
<tr>
<td>RSDC(2)-GARCH</td>
<td>-12764</td>
<td>27</td>
<td>2531</td>
<td>10.107</td>
<td>10.170</td>
<td>10.130</td>
</tr>
<tr>
<td>RSDC(3)-GARCH</td>
<td>-12734</td>
<td>38</td>
<td>2531</td>
<td>10.092</td>
<td>10.180</td>
<td>10.124</td>
</tr>
<tr>
<td>RSDC(2)-GJR</td>
<td>-12794</td>
<td>27</td>
<td>2531</td>
<td>10.131</td>
<td>10.193</td>
<td>10.154</td>
</tr>
<tr>
<td>RSDC(3)-GJR</td>
<td>-12763</td>
<td>38</td>
<td>2531</td>
<td>10.115</td>
<td>10.203</td>
<td>10.147</td>
</tr>
</tbody>
</table>

* Akaike Info Criterion ** Schwarz Criterion ***Hannan-Quinn Criterion

Considering the results of this section together with the analyzes from the previous section, the RSDC(3)-GJR model showed greater instability and uncertainty about the determination of the regime at each point in time, thus, the RSDC(2)-GJR model was chosen as the most suitable for the purposes of this study and, as a consequence, the final conclusions are based, mainly, on its results.

6 Conclusion

Given the main objective of this study that is to analyze, from an econometric perspective, the phenomenon of financial contagion between stock market returns of different countries, we employed a methodology originally developed by Pelletier (2006), named Regime Switching Dynamic Correlation (RSDC) model. A modification was made in the original RSDC model, the introduction of the GJR-GARCH model formulated in Glosten, Jagannathan and Runkle (1993), on the equation of the conditional univariate variances to allow asymmetric effects in volatility be captured. Throughout the work this methodology was applied to daily returns of SP500 (United States), Bovespa Index (Brazil), FTSE100 (UK) and KOSPI (Korea) for the period from 02/01/2003 to 09/20/2012 and confronted with other models most widespread in the literature on the subject.

The results comparison revealed that the adapted RSDC model presented gains in likelihood when compared with the Constant Conditional Correlation (CCC) model proposed by Bollerslev (1990) and the Dynamic Conditional Correlation (DCC) model developed in Engle (2002) for the series and sample period selected. The determination of the number of regimes for the adapted RSDC model was made based on information criteria, the stability of the regimes and the degree of uncertainty about the definition of the regime that
is in place at each instant of time. Thus, the GJR-RSDC model with two regimes was defined as the most appropriate due to the better performance in general.

The results of the RSDC(2)-GJR model revealed that the correlation matrix of the regime ranked as higher volatility (turbulence) presents statistically higher correlation coefficients than the calm regime for all pairs of stock market returns. Considering the World Bank definition of financial contagion titled very restrictive, which says that contagion occurs when correlations between countries increase during periods of crisis with respect to correlations in tranquil periods, the set of results provide evidence for the existence of financial contagion between the markets of the four countries. Such a conclusion should be evaluated with caution, since the non-use of macroeconomic variables or economic fundamentals in the modeling process (mean equation) is a limitation of the approach chosen. As discussed in Chapter 2, it was assumed as a premise, that these factors or economic mechanisms would not be able to transmit the effects of the crises observed between 2003 to 2012 this quickly and abruptly.

The smoothed probabilities of each regime have relative stability and low uncertainty to determine which regime prevails at each instant of time. This conclusion shows that the transition between regimes occurs not gradually but abruptly. Moreover, it was possible to observe two different patterns of behavior throughout the sample. During the years 2003 to mid-2007 it is possible to observe a dominance of the regime categorized as calm (state 1). These long periods of low volatility are interrupted by some points of turbulence. One possible interpretation is that a turbulence shock in a country is transmitted to other markets, but when the intensity and direction are recognized, the correlation level fall like a temporary financial shock. In contrast, for the period from mid-2007 until 2012, the higher volatility state prevails in almost all observations and suggests that the financial crises events entailed permanent changes. In summary, the average duration of high volatility periods is greater in the second half of the sample.

Among the suggestions for expanding this work is possible to highlight the use of macroeconomic variables in the conditional mean equation of each stock market return series, as proposed in Pesaran and Pick (2007) and Marcal et al (2011), aiming to separate more precisely the concept of contagion and interdependence, without having to be assumed any premise. Alternatively, in case of difficulties in determining the economic fundamentals, it could be employed factor models that do not require the specification of such variables. Another suggestion would be the application of multivariate models of volatility with regime switching Markov analysis to the phenomenon known in the literature as herding.
References


