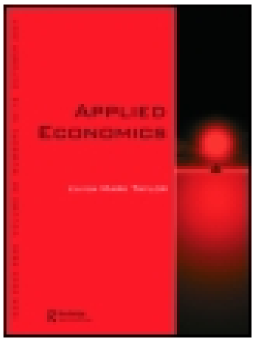

Applied Economics

ISSN: 0003-6846 (Print) 1466-4283 (Online) Journal homepage: http://www.tandfonline.com/loi/raec20

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APPLIED ECONOMICS, 2015
http://dx.doi.org/10.1080/00036846.2015.1119794

Routledge
Taylor & Francis Group

Analysis of contagion from the dynamic conditional correlation model with Markov Regime switching

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ABSTRACT
Over the last decades, the transmissions of international financial events have been the subject of many academic studies focused on multivariate volatility models. This study evaluates the financial contagion between stock market returns. The econometric model employed, regime switching dynamic correlation (RSDC). A modification was made in the original RSDC model, the introduction of the GJR-GARCH-N and also GJR-GARCH-*t* models, on the equation of conditional univariate variances, thus allowing us to capture the asymmetric effects in volatility and also heavy tails. A database was built using series of indices in the United States (S&P500), the United Kingdom (FTSE100), Brazil (IBOVESPA) and South Korea (KOSPI) from 1 February 2003 to 20 September 2012. Throughout this study the methodology is compared with those frequently found in literature, and the model RSDC with two regimes was defined as the most appropriate for the selected sample with *t*-Student distribution in the disturbances. The adapted RSDC model used in this article can be used to detect contagion – considering the definition of financial contagion from the World Bank called very restrictive – with the help of the empirical exercise.

KEYWORDS
Contagion; multivariate volatility models; Markovian switching regime; GARCH-GJR-*t*

JEL CLASSIFICATION
G15; C59; F36

I. Introduction

Globalization, deregulation and technological advances have deeply changed relationships in international financial markets. There is sufficient evidence to support the argument that the increasing velocity of information transmission is partially responsible for inducing stronger stock market integration. On closer inspection, there are questions about the possible 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 policymakers and international investors seeking to diversify risks. In the last two decades, patterns in the international spread of financial events have been the subject of many academic studies, particularly empirical research focused on volatility.

In this context, the goal of this study is to evaluate the degree of 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 (CCC) model proposed by Bollerslev (1990) and the 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-N and also GJR-GARCH-*t* models, formulated in Glosten, Jagannathan, and Runkle (1993), on the equation of the conditional univariate variances to allow asymmetric effects in volatility be captured and also heavy tails. Note that identifying possible causes or predicting the economic consequences of financial contagion is not part of this study.

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The RSDC model structure incorporates the decomposition of covariance matrices into SDs and correlations. The correlation matrix follows a regime switching model and, therefore, stays constant within a regime, but different across regimes. Transitions between these regimes are governed by a Markov chain. The central concept in this 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 nonlinear structure when considering the entire procedure.

Besides the features described earlier, there are two main arguments for choosing the RSDC model as an alternative to dynamic conditional correlation (DCC). The first concerns the absence of the need to define *a priori* the periods of financial crises, because the RSDC model incorporates regime changes in its dynamics. This procedure is made endogenously, since the latent Markov state variable determines the regime prevailing 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 has been used for contagion tests over the last decade but, as far as we know no comparison with RSDC has been done in testing for contagious. To complement the analysis of this work, a comparison between the results of both models is presented in Section V.

The database was built with the series of daily closing stock market indices in the United States (SP500), the United Kingdom (FTSE100), Brazil (IBOVESPA) and South Korea (KOSPI) from 1 February 2003 to 20 September 2012. The reason for choosing these countries was to include two representatives developed markets (Europe and North America) and two representative emerging markets (South America and Asia).

The rest of the article is organized as follows. Section II presents literature review on the definitions of contagion and econometric approaches. Section III outlines the econometric methodology employed. The Sections IV and V describe the database and the main results, respectively. Finally, Section VI summarizes the main conclusions of this work.

II. Literature review

Contagion definition

In the last two decades, the analysis of traditional patterns of international spread of financial events has become a target of academic attention on modelling volatility. Almost all studies have a primary difficulty: the absence of a common definition of financial contagion.

Evidence of heterogeneity in definitions can be illustrated by Pericoli and Sbracia (2003), which suggests five different definitions of contagion: significant increase in the probability of a crisis in one country conditional on the existence of a crisis in another country; overflow (spillover) of volatility from a country in crisis to the financial markets of other countries; strong growth of co-movements in prices and quantities across markets, conditional on a crisis in one market or group of markets; changes in the channels transmitting shocks across markets; excess of co-movements not explained by economic fundamentals.

A substantial part of 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 (2006), Pesaran and Pick (2007) and Marçal et al. (2011). Masson (1998) suggested a three-category classification. The first category, monsoonal effects, suggests that financial crises seem to be contagious because of the correlation between the macroeconomic variables in 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 two categories illustrate situations of interdependence. Finally, the third category, referring to the theory of pure contagion defines a situation where a crisis in one country can cause a crisis in another country without affecting the economic fundamentals between them.

The World Bank[1] offers three definitions of contagion: broad, restrictive and very restrictive. In the broad definition, contagion is the cross-country transmission of shocks, or the general cross-country spillover effects of economic shocks. Contagion can

[1]Available at World Bank site: http://worldbank.org. Direct link to the definitions http://go.worldbank.org/JIBDRK3YC0.

occur during both good and bad times. In such cases, contagion does not need to be related to crises. In the restrictive definition, contagion is the transmission of shocks to other countries or the cross-country correlation, beyond any fundamental links between countries and beyond common shocks. This definition is usually referred to as excess co-movement, commonly explained by herding behaviour. In the very restrictive definition, contagion occurs when cross-country correlations increase during crisis times relative to correlations during tranquil times. This definition can be interpreted as the breakdown in the transmission mechanism occurring during a period of turbulence, also commonly called shift-contagion.

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

In the econometric methodology, presented in Section III, the nonuse of macroeconomic variables or economic fundamentals reveals that a premise is adopted: that these factors or mechanisms would not be able to transmit the effects of crises observed from 2003 to 2012 so quickly and abruptly. In Section VI, a reference is made to this question, that is directly related to the distinction between the definition of interdependence and contagion, as a suggestion for future study.

Econometric approaches

Just as there is no uniformity in the definition of financial contagion, there is no consensus in the literature about the econometric methodology best employed for analysing contagion. Among the major studies on the subject, it is possible to highlight 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 from 29 countries. Using the same database, Corsetti, Pericoli, and Sbracia (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) comprised traditional techniques of factor models combined with stochastic volatility models to study dependence between stock price indices in Latin and North America. Dungey et al. (2004) provides a detailed review of methodologies based on very close definitions of contagion in a way that it is possible to build a homogeneous framework highlighting 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) extend 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 financial empirical research. Nevertheless, the first order of obstacles arise when considering large dimension specifications due to the complexity of computational procedures needed to estimate parameters resulting from a high number of coefficients. Such difficulties have encouraged many academic studies to submit enhancements and alternatives to traditional multivariate GARCH models.

One of the most widely used multivariate volatility models is the 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 conditional correlations are constant over time. The advantage is that 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 proposed a GARCH-type dynamic model for correlation matrices. Such model, named DCC has numerical stability even for large dimensional problems because, similar to CCC, the estimation procedure can be performed in two stages. The main benefit of correlation models over the BEKK and VEC specifications is the parsimony in parameterization, which overcomes the barriers to implement models in dimensions larger than the bivariate one. The studies that used these multivariate volatility models for the investigation of contagion include Lombardi et al. (2004), Marçal 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. Pelletier (2006) developed the RSDC model that serves as the basis for the methodology used in the present article. RSDC allows the unconditional correlation to be conducted by an unobservable component characterized 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 DCC (MS-DCC), which enables 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 such as CCC and DCC.

Finally, it is worth mentioning the paper of Chen (2009) which also applies the RSDC model proposed by Pelletier (2006) for a series of US 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 switching would significantly complicate the already complicated estimation process. The number of observations in each regime would not be sufficient to achieve a robust estimation of DCC. Idier (2009) also made reference to the fact that adding more than 10 extra parameters may not produce a great improvement and, thus, this formulation (MS-DCC) was not chosen as the central conductor of this study. To conclude, the RSDC (or MS-CCC) model would be sufficient to capture the dependency on the correlation.

III. Methodology

RSDC model

The methodology used in this study is based on the RSDC model proposed by Pelletier (2006). It is the combination of the CCC model presented by Bollerslev (1990) and the Markov regime switching suggested by Hamilton and Susmel (1994). We modified the original RSDC, by introducing GJR-GARCH[2] in the equation of conditional univariate variances thereby allowing the asymmetric effects in volatility to be captured. The GJR-GARCH model was formulated by Glosten, Jagannathan, and Runkle (1993).

In the CCC model, conditional covariances are parameterized to be proportional to the product of the corresponding SDs. The covariances of a vector of returns are decomposed into SDs and correlations. Thus, both the computational processing required for estimation is reduced and the imposition of conditions to ensure that the covariance matrix is positive semi-definite becomes simpler. Nevertheless, a major assumption of the model is that 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 SDs and correlations, but the correlations have some dynamic. The correlation matrix follows a regime switching model and, therefore, stays constant within a regime, but different across regimes. Transitions between these regimes are governed by a Markov chain. The CCC model can be considered as 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 DCC model formulated by Engle (2002) and Tse and Tsui (2002), which uses the same decomposition of the covariance matrix of Bollerslev (1990). However, instead of assuming constant correlation, the authors propose that these are characterized according to a GARCH-type dynamic model. According to Pelletier (2006), it is reasonable to question whether a GARCH-type approach for

[2]In 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 nonlinearities that will prohibit analytic computation of conditional expectations.

correlations would be more appropriate because the dynamics of the correlation may be inherently different from the behaviour of a covariance. For instance, correlations have upper and lower limits, whereas 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 in unconditional volatility. In Section V, there is an exercise performed with dummies to offer evidence on the issue of persistence.

In addition to the points raised, and as stated in Section I, there are two fundamental aspects influencing the selection of the RSDC model over the DCC model. 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 into its dynamics. This procedure is made endogenously, since the latent Markov state variable determines the regime that prevails at each instant of time. The second is the idea that (probably) the contribution to the literature could be higher, given that DCC is already very widespread and used for contagion tests performed in the last decade. To complement the analysis of this work, a comparison between the results of both models is presented in Section V.

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

$$Y_t = H_t^{\frac{1}{2}} U_t \tag{1}$$

where U_t is an independent and identically distributed process with zero mean and variance–covariance matrix I_K[3]. The time-varying covariance matrix H_t can be decomposed into:

$$H_t = S_t \Gamma_t S_t \tag{2}$$

where S_t is a diagonal matrix composed of the SDs $\sigma_{k,t}$ with $k = 1, \ldots, K,$ and Γ_t is the correlation matrix.

Each variance $\sigma_{k,t}$ is modelled by a univariate GARCH. In this study, unlike Pelletier, we use the GJR-GARCH model to capture the negative skewness, as follows:

$$\sigma_{k,t}^2 = \omega + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{o} \gamma_j \cdot I(\varepsilon_{t-j}) \cdot \varepsilon_{t-j}^2 + \sum_{l=1}^{p} \beta_i \sigma_{t-l}^2 \tag{3}$$

where

$$I(\varepsilon_{t-j}) = \begin{cases} 1 & \text{if } \varepsilon_{t-j} < 0 \\ 0 & \text{otherwise} \end{cases}$$

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

$$\Gamma_n = \begin{pmatrix} 1 & \rho_{12} & \cdots & \rho_{1k} \\ \rho_{21} & 1 & \cdots & \rho_{2k} \\ \vdots & \vdots & \ddots & \vdots \\ \rho_{k1} & \rho_{k2} & \cdots & 1 \end{pmatrix}, \ \Gamma_t = \sum_{n=1}^{N} I_{[\Delta_t = n]} \cdot \Gamma_n \tag{4}$$

where Δ_t is a random variable independent of U_t which is defined as a state variable. This state variable follows a first order Markov process and can assume only integer values $\{1, \ldots, N\}$. This representation of Γ_t shows another advantage of the RSDC model. At the estimation stage, the correlation matrix Γ_t may have only N different configurations, and hence need to be inverted only N times, whereas 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 Δ_t be equal to j is given only as a function of Δ_{t-1}, that is:

$$P(\Delta_t = j | \Delta_{t-1} = i) = p_{ij} \tag{5}$$

with the constraint:

$$p_{i1} + p_{i2} + \cdots + p_{iN} = 1$$

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

$$\Pi = \begin{pmatrix} p_{11} & p_{12} & \cdots & p_{1N} \\ p_{21} & p_{22} & \cdots & p_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ p_{N1} & p_{N2} & \cdots & p_{NN} \end{pmatrix} \tag{6}$$

The regime switching model allows calculation of the expected duration in each regime, denoted by D_i for $i = 1, \ldots, N$. This is the average length of each regime conditioned on the information of being in a specific regime, and it is given by

[3]It is assumed that the distribution is normal or *t*-Student.

$$E(D_i) = \frac{1}{1 - p_{ii}} \tag{7}$$

Other valuable information that can be extracted from the model is the ergodic probability of each regime, that is the probabilities associated with each state in equilibrium. This can be obtained follows:

$$\pi = \Pi \cdot \pi \tag{8}$$

$$\begin{pmatrix} \pi_1 \\ \pi_2 \\ \vdots \\ \pi_N \end{pmatrix} = \Pi \cdot \begin{pmatrix} \pi_1 \\ \pi_2 \\ \vdots \\ \pi_N \end{pmatrix}$$

with

$$\sum_{i=1}^{N} \pi_i = 1$$

$$\pi_i \geq 0$$

Estimation

According to Pelletier (2006), theoretically the RSDC model can be estimated in one step by calculating the following expression to maximize the likelihood:

$$QL(\theta; Y) = \sum_{t=1}^{T} \log f(Y_t | Y_1^{t-1}) \tag{9}$$

where $Y_1^{t-1} = \{Y_{t-1}, Y_{t-2}, \cdots, Y_1\}$ and θ is the vector of parameters. The computation of Equation 9 is performed using the Hamilton's filter presented in Hamilton (1989), because the state variable Δ_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, the present study applies the two-step estimation procedure.

The total space of parameters θ can be separated in space θ_1, referring to the parameters of the univariate volatility models for marginal distributions, and θ_2, for the parameters in the correlation model. Denoting QL_1 as the likelihood of parameter space θ_1 and QL_2 as the likelihood of parameter space θ_2, we have:

$$QL_1(\theta_1; Y) = -\frac{1}{2} \sum_{t=1}^{T} (K\log(2\pi) + 2\log(|S_t|) + U'_t U_t) \tag{10}$$

$$\begin{aligned} QL_2(\theta_2; Y) = & -\frac{1}{2} \sum_{t=1}^{T} (K\log(2\pi) \\ & + 2\log(|\Gamma_t|) + U'_t \Gamma_t^{-1} U_t) \end{aligned} \tag{11}$$

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 Hamilton's filter.

Maximizing QL_2, unlike QL_1, requires the application of the Hamilton's filter, as the state variable Δ_t is an unobserved component as mentioned before. Since the number of parameters in the correlation model grows quadratically with the number of series involved, the direct maximization of QL_2 when Γ_t has a high dimension may not be simple. To solve this problem, it is possible to use expectation maximization (EM) (see the discussion in Section 3.2 of Pelletier (2006)).

IV. Dataset

Description

The database construction involved the collection[4] of daily closing stock market indices from the United States (SP500), the United Kingdom (FTSE 100), Brazil (Bovespa Index) and South Korea (KOSPI) from 1 February 2003 to 20 September 2012, as illustrated in Fig. 1. The reason for choosing these countries was to include two representatives developed markets (Europe and North America) and two representative emerging markets (South America and Asia).

Regarding the sample definition, the intention was to select an extensive set of historical data of approximately a 10-year period. This required 2536 observations for each series and was characterized by the presence of financial crisis events, particularly the US subprime mortgage crisis of 2008 and the worsening European debt crisis 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 switching model can determine endogenously

[4]Data obtained by Reuters Ecowin system from the following codes: usa15510 (sp500); brc15500 (ibov); gbr15500 (ftse100) and krw15500 (kospi).

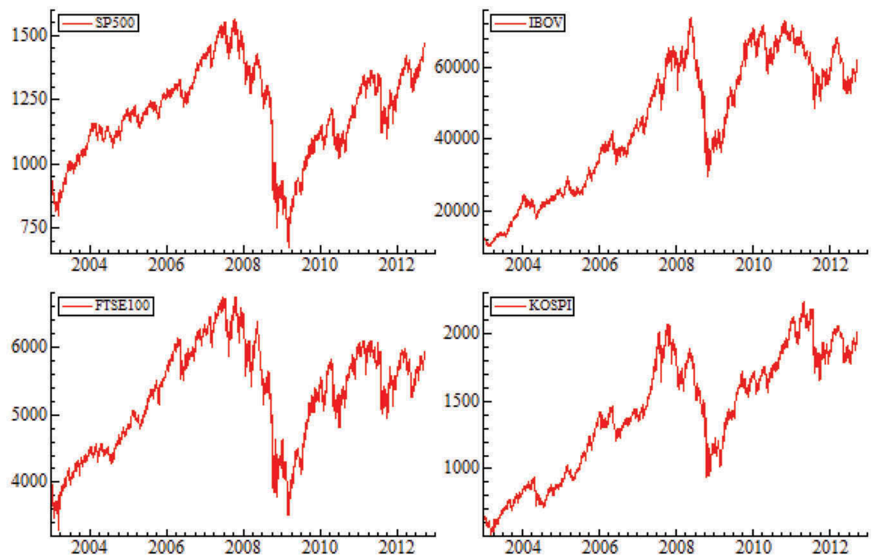

Figure 1. Stock market indices.

such periods. The stock market indices' graphs illustrate the behaviour of each series and reveals a greater range of values for the second half of the sample. Furthermore, a preliminary visual analysis shows a joint decrease of all series during the crisis mentioned earlier.

Initial analysis

Before the estimation stage, the initial database underwent some treatments. The first was to estimate a local level model for each series to impute an estimate for missing values (missing data) related to the days where the markets were closed because of holidays.[5] The missing values were replaced by the smoothed estimates of the component level.[6]

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

The third treatment involved the synchronization of trading days to account for time zone differences. With respect to Greenwich time (GMT), Seoul is GMT + 9, and thus operationally 1 day ahead of negotiations in the other regions. Following Santos and Valls Pereira (2011), data synchronization respected the following rule: $[\text{SP500}_t,\ \text{IBOV}_t,\ \text{FTSE}_t,\ \text{KOSPI}_{t+1}]$ and the stock market returns are presented in Fig. 2.

An analysis of the descriptive statistics, graphs and histograms of the returns confirms the stylized facts of financial time series. The sampling distributions of the four returns series are characterized by heavier tails (leptokurtic) than a normal distribution, with a mean close to zero and volatility clustering. Also, all returns reported negative asymmetry.

Filtering

Although volatility models have as its premise the absence of serial correlation as their premise, 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, are statistically different from zero. In order to model the autocorrelation structure of the data, we filtered for the conditional mean through the estimation of ARMA(p, q) models.

The determination of the order p and q of these models was done together with the GARCH models and 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, the LM test corroborates the conclusion of no serial autocorrelation. Finally, we calculated the statistics for the ARCH

[5]Number of missing data: SP500-87, IBOVESPA-124, FTSE100-79 and KOSPI-118.
[6]This procedure was done with the software package OxMetrics STAMP 8.2, as suggested by Koopman et al. (2009).

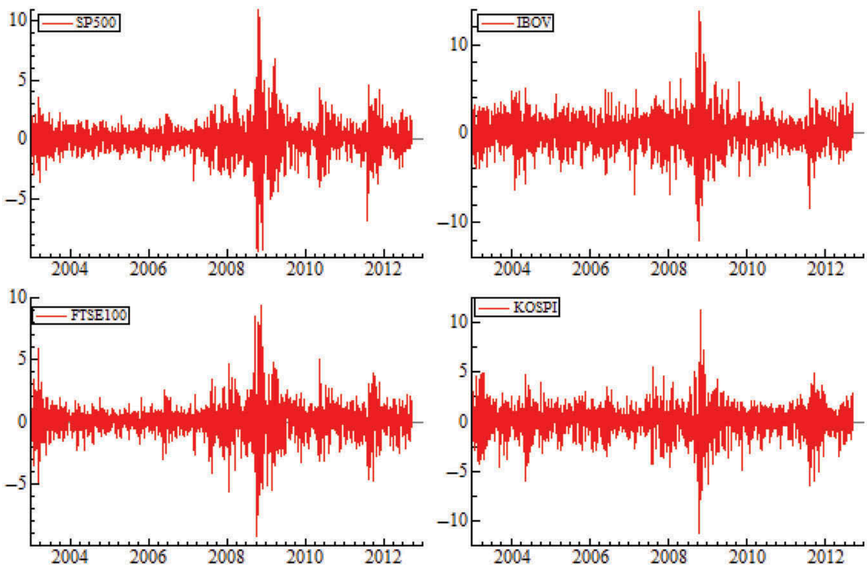

Figure 2. Stock market returns.

heteroscedasticity test and the null hypothesis of no heteroscedasticity is rejected justifying the application of volatility models in this study.

Before presenting Table 1, it is important to comment about the number of observations in the sample after the database treatment and the filtering process, in order to have the same number of observations to be able to use information criterion to choose between models. During treatment, 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 three more observations losses. Thus, the final sample included 2531 observations from 8 January 2003 to 19 September 2012.

V. Results

RSDC model

Marginal distribution

After filtering for the conditional mean of the series through the estimation of the ARMA(p, q) models presented in 'Filtering' section, we estimated the GJR-GARCH models for the univariate variance equation of each series. As mentioned earlier, the introduction of the GJR-GARCH model at this stage comprises a modification to the original RSDC developed by Pelletier (2006). This change allowed to capture the asymmetric effects more effectively.[7] The coefficient estimates and SEs are reported in Table 2[8] as well as the persistence λ and the half-life (HL) of the series

Table 1. Residual tests.

		Autocorrelation[a]				Heteroscedasticity[b]			
	(p, q)	L(1)	L(3)	L(6)	L(9)	L(1)	L(3)	L(6)	L(9)
S&P	(3, 3)	0.01	0.73	0.70	1.88	99.0	201.8	165.3	120.5
		(0.91)	(0.53)	(0.65)	(0.05)	(0.00)	(0.00)	(0.00)	(0.00)
IBOV	(2, 3)	1.20	1.37	1.05	1.20	83.6	176.2	115.5	99.5
		(0.27)	(0.24)	(0.39)	(0.29)	(0.00)	(0.00)	(0.00)	(0.00)
FTSE	(3, 3)	1.15	0.95	1.16	1.34	138.4	157.7	104.0	73.7
		(0.28)	(0.41)	(0.32)	(0.20)	(0.00)	(0.00)	(0.00)	(0.00)
KOSPI	(3, 3)	0.10	0.88	1.33	1.54	111.5	84.8	123.6	85.0
		(0.75)	(0.44)	(0.23)	(0.12)	(0.00)	(0.00)	(0.00)	(0.00)

Notes: [a]*F*-statistics and *p*-value for LM test for serial correlation.
[b]*F*-statistics and *p*-value for ARCH test for heteroscedasticity.

[7]There are other types of GARCH models that are capable of capturing asymmetry such as EGARCH in Nelson (1991), TGARCH in Zakoian (1994) and QGARCH in Sentana (1995) and others.
[8]Only the results for the *t*-Student distribution for the disturbances is presented.

Table 2. Univariate GJR-GARCH(1,1)-*t*.

	ω	α	γ	β	v^a	λ	HL
S&P	0.0123 (0.0022)	−0.0181 (0.0085)	0.1458 (0.0156)	0.9341 (0.0086)	8.3782 (1.3474)	0.989	63
IBOV	0.0931 (0.0187)	0.0092 (0.0126)	0.1286 (0.0205)	0.8951 (0.0149)	10.5835 (1.9407)	0.969	23
FTSE	0.0154 (0.0029)	−0.0057 (0.0109)	0.1664 (0.0185)	0.9103 (0.0103)	14.4647 (3.8982)	0.988	58
KOSPI	0.0676 (0.0098)	−0.0229 (0.0110)	0.2072 (0.0246)	0.8844 (0.0128)	8.4032 (1.4838)	0.965	21

Notes: GJR-GARCH(1,1)-*t* is the model with *t*-Student distribution.
[a]Degrees of freedom of the *t*-Student distribution.

computed according to the formulas given later. The term γ is the coefficient of skewness specified in Equation 3.

$$\lambda = \alpha + \beta + \frac{\gamma}{2} \tag{12}$$

$$HL = 1 - \left(\frac{\log(2)}{\log(\lambda)}\right) \tag{13}$$

The graph of the estimated conditional variances in this first stage can be viewed in Fig. 3.

The GJR-GARCH(1,1) model estimates reveals an often found result in the empirical finance literature, a high persistence and high half-life, as in Table 2. According to Diebold (1986), this high persistence may be associated with no observed changes in the unconditional volatility over time. The relevance of this point is that the change in unconditional volatility would be evidence of changes in the unconditional correlation between the series over the sample, which justifies the application of the regime switching model.

Similar to Almeida and Valls Pereira (1999), an *ad hoc* dummy d_1 was created with a value 1 for the period from January 2008 to June 2009, and 0 for the rest, based only on visual inspection. The idea was to show that the inclusion of an intercept dummy in the equation of univariate variances can change the persistence and the half-life of the series, thus providing further evidence of changes in the unconditional volatility over time. With this objective, the GARCH models were recalculated for the marginal distributions, but this time by incorporating the dummy in each equation. The results in Table 3 show a reduction of persistence and half-life of the four series using the *t*-Student distribution for the disturbances. On average, the persistence decreases from 0.98 to 0.97 and half-life decreases from 42 to 32 days. Moreover, in all cases the dummy was statistically significant.

Returning to Equation 3, the GJR-GARCH(1,1) model specification with dummy and q, o and p equal to 1 followed:

$$\sigma^2_{k,t} = \omega_0 + \omega_1 \cdot d_1 + \sum_{i=1}^{q} \alpha_i \varepsilon^2_{t-i} + \sum_{j=1}^{o} \gamma_j \cdot I(\varepsilon_{t-j}) \cdot \varepsilon^2_{t-j} + \sum_{l=1}^{p} \beta_i \sigma^2_{t-l} \tag{14}$$

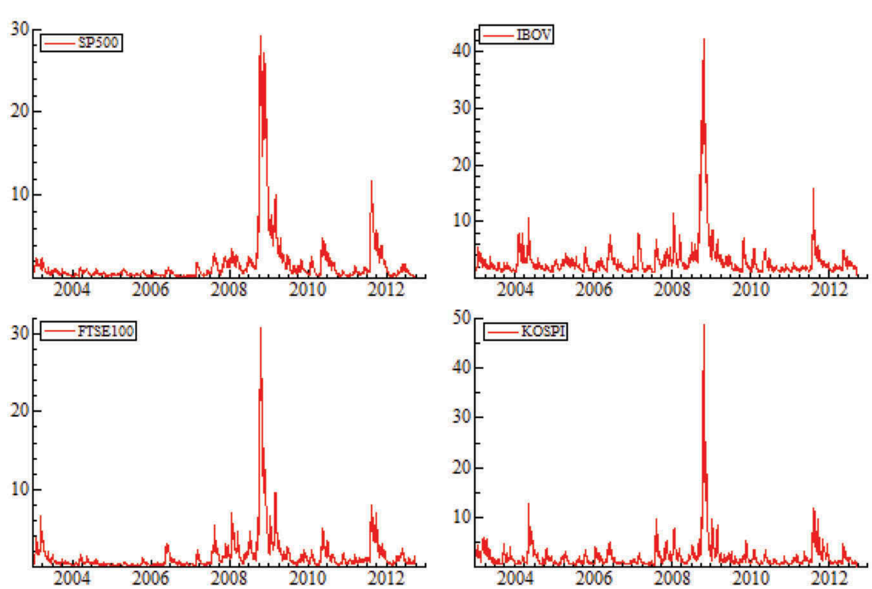

Figure 3. Conditional variances for GJR-*t*.

Table 3. Univariate GJR-GARCH(1,1)-*t* with dummies.

	ω_0	ω_1	α	γ	β	v^a	λ	HL
S&P	0.0143 (0.0025)	0.0297 (0.0160)	−0.0192 (0.0085)	0.1476 (0.0162)	0.9298 (0.0097)	8.5767 (1.3970)	0.984	45
IBOV	0.1233 (0.0253)	0.1660 (0.0610)	−0.0014 (0.0132)	0.1485 (0.0235)	0.8738 (0.0191)	11.2526 (2.1376)	0.947	14
FTSE	0.0203 (0.0036)	0.0527 (0.0192)	−0.0092 (0.0117)	0.1644 (0.0208)	0.8962 (0.0128)	16.8569 (5.6504)	0.979	34
KOSPI	0.0752 (0.0109)	0.0466 (0.0268)	−0.0258 (0.0110)	0.2152 (0.0260)	0.8757 (0.0144)	8.4614 (1.5011)	0.979	34

Notes: GJR-GARCH(1,1)-*t* is the model with *t*-Student distribution.
[a]Degrees of freedom of the *t*-Student distribution.

Two regimes[9]

After the marginal distributions modelling stage, we estimate the correlation matrices with the assumption of only two regimes. In the next section, we estimate the correlation matrices with the assumption of three regimes. The regime identified as state 1 is defined as high volatility (turbulence), while that identified as state 2 is defined as low (see Table 4) volatility (calm, see Fig. 4). The transition probability matrix Π indicates that the regimes are persistent in duration[10] because the probability of being in state 1 at time $t+1$ is conditional on being at that same state at time t is 0.992 and the similar for the second state is 0.984. Returning to Section III, these values are given, respectively, by the probabilities p_{11} and p_{22} defined by Equation 5. Using Equation 7, the higher persistence of state 1 reflects a greater average expected duration $E(D_1)$ of this regime, 125 days against 62 days of state 2. With respect to the number of observations in each regime, state 1 also has a greater number of points, 1676 against 855 in the other regime. From the ergodic probabilities of each regime calculated from Equation 8, it can be observed that the probability of state 1 is 0.65 and higher than that of state 2 (0.35).

Table 4. Transition matrix with two regimes, ergodic probabilities and expected duration for GARCH-GJR-*t*.

Π	$\Delta_t = 1$	$\Delta_t = 2$		Observations	π	$E(D)$
$\Delta_{t-1} = 1$	0.992	0.008 (0.004)	$\Delta_t = 1$	1676	0.65	125
$\Delta_{t-1} = 2$	0.016 (0.013)	0.984	$\Delta_t = 2$	855	0.35	62

The correlation matrices defined in Equation 4, reported in Table 5, provide some evidence of financial contagion according to the definition adopted in this study.[11] The matrix Γ_1, associated with the high volatility state, presents significantly higher correlation coefficients than Γ_2 associated with calm peri-

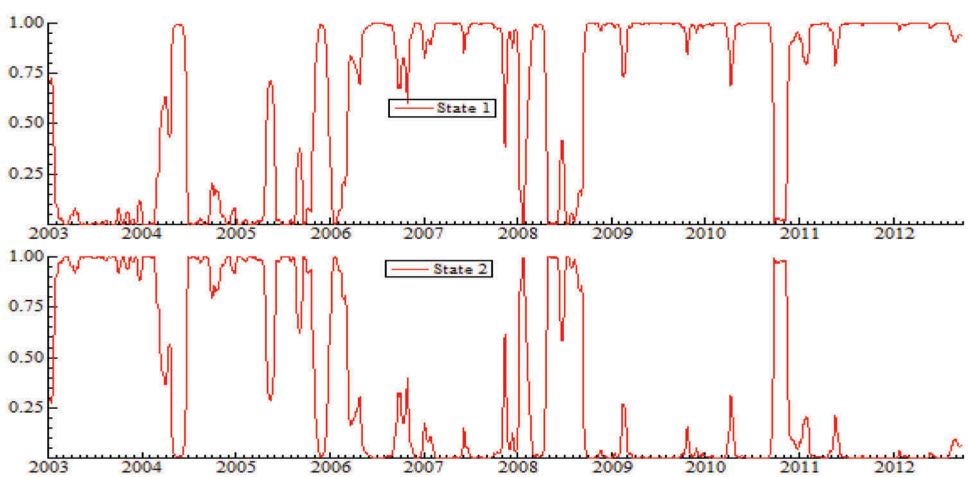

Figure 4. Smoothed probabilities with two regimes with *t*-Student distribution.

[9]For the two regimes it is reported only the *t*-Student distribution for the disturbances.
[10]It is used persistence in duration to mean: the state with higher probability will have a higher average duration implies a higher persistence (in duration) than the model with a smaller average duration.
[11]Another way to test contagiousness is to use MSVAR with constant variance within regimes as it is done in Mandilaras and Bird (2010).

Table 5. Correlation matrices for two regimes with *t*-Student distribution for disturbances.

Γ_1	SP500	IBOV	FTSE	KOSPI	Γ_2	SP500	IBOV	FTSE	KOSPI
SP500	1.000				SP500	1.000			
IBOV	0.754 (0.049)	1.000			IBOV	0.467 (0.045)	1.000		
FTSE	0.642 (0.051)	0.592 (0.039)	1.000		FTSE	0.404 (0.040)	0.286 (0.065)	1.000	
KOSPI	0.448 (0.056)	0.432 (0.064)	0.345 (0.087)	1.000	KOSPI	0.290 (0.022)	0.222 (0.033)	0.225 (0.027)	1.000

ods. As an example, the pair S P500 and Bovespa Index has a correlation coefficient of 0.47 in the calm regime and 0.75 in the turbulence state. It is noteworthy that the estimate SEs of the correlation coefficients between FTSE100 and KOSPI, implies that the correlation in the first regime is not bigger than the second regime so it is not possible to assert that there is strong evidence of contagion between the two markets.[12]

The analysis of the smoothed probabilities' graphs reveals that these do not move very often between the regimes and, as a consequence, exhibit relative stability. Furthermore, there is low uncertainty to determining the regime prevailing at each instant of time, given that the probabilities are concentrated around 0 or 1 at each observation. This finding shows that the transition between regimes occurs not gradually but abruptly.

Another interesting aspect is the changing regime dominance pattern throughout the sample period. From 2003 to the end of 2005, a dominance of the regime categorized as calm (state 2) can be observed. These long periods of low volatility are interrupted at some points by turbulence. A possible interpretation is that a turbulence shock in one country is transmitted to other markets, but when the intensity and direction are recognized, the correlation level falls similar to a temporary financial shock. In contrast, from the beginning of 2006 to 2012, the higher volatility state prevails in almost all observations, suggesting that financial crises occurring during that period entailed permanent changes. In summary, the average duration of high volatility periods is greater in the second half of the sample.

Three regimes

This section presents the results for the correlation matrices with the assumption of three regimes.[13] As will be detailed, the model with three regimes showed greater instability and uncertainty about the definition of the regime prevailing at each point in time, see Fig. 5. In addition, estimate SEs increased and did not result in the same strong conclusions of the case with only two regimes.

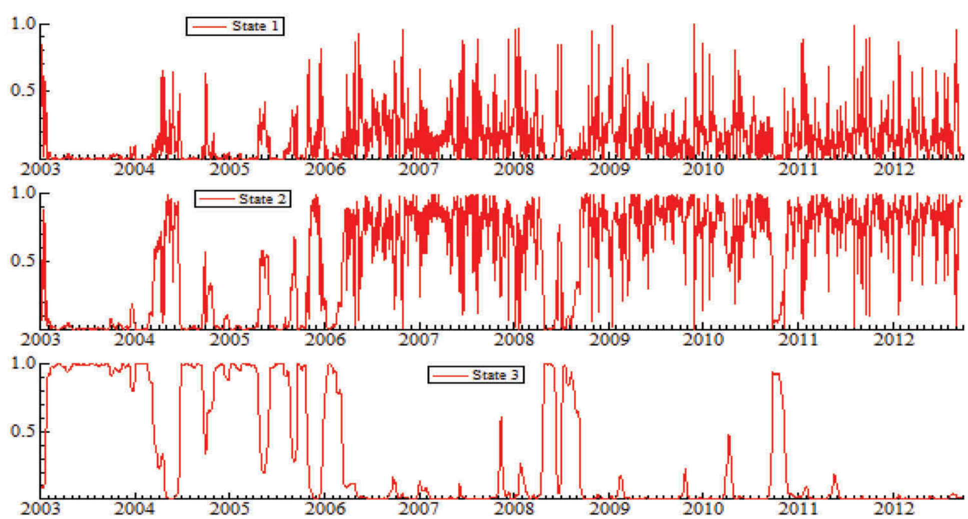

Figure 5. Smoothed probabilities with three regimes with normal distribution.

[12]This is because the confidence interval for the two values intercept.
[13]For the three regimes, only the normal distribution in the disturbances is reported.

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 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 probability transition matrix Π (see Table 6) shows that the regimes of state 1, state 2 and state 3 are characterized, by low, moderate and high persistence, given that $p_{11} = 0.46$, $p_{22} = 0.87$ and $p_{33} = 0.98$, respectively. The differences in persistence impact directly on the average expected duration $E(D)$ of each regime which is 2 days for state 1, 8 days for state 2 and 48 days for state 3. The Markov chain spends most of its time in the turbulent regime, which has 1585 observations versus 814 in state 3 and 132 in 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 $\pi_3 = 0.32$).

The correlation matrices, reported in Table 7, give some evidence of financial contagion, according to the definition adopted in this study, but less incisive than in the case of two regimes. The matrix Γ_2, associated with the high volatility state, presents significantly higher correlation coefficients than Γ_3, related to tranquil periods. Nonetheless, the distinction between matrix Γ_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 SEs. Nevertheless, comparing both numbers with the coefficient 0.58 (SE 0.17) of the medium volatility regime, we cannot sustain the same assertion. In certain cases, we can even observe an inversion. Pairs KOSPI and IBOVESPA as well as KOSPI and FTSE100, in matrix Γ_1, have higher coefficients than Γ_2, which is not expected originally. A possible interpretation for these results must concern the difficulty in determining the regime prevailing at each instant of time, as discussed immediately below. Before that, it is also important to note that the estimate SEs of the correlation coefficients between the pairs are generally higher than those of matrices with two regimes.

Analysis of the smoothed probabilities' graphs reveals high uncertainty regarding the definition of the regime that is in place at each instant of time, especially for 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. This argument, as previously mentioned, may help explain the results for the correlation matrices.

Another relevant aspect is that due to the lower average expected 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

Table 6. Transition matrix with three regimes, ergodic probabilities and expected duration with normal distribution.

Π	$\Delta_t = 1$	$\Delta_t = 2$	$\Delta_t = 3$		Observations	π	$E(D)$
$\Delta_{t-1} = 1$	0.462	0.488 (0.343)	0.050 (0.080)	$\Delta_t = 1$	132	0.13	2
$\Delta_{t-1} = 2$	0.126 (0.046)	0.872	0.000 (0.017)	$\Delta_t = 2$	1585	0.55	8
$\Delta_{t-1} = 3$	0.008 (0.017)	0.013 (0.030)	0.979	$\Delta_t = 3$	814	0.32	48

Table 7. Correlation matrices for three regimes.

Γ_1	SP500	IBOV	FTSE	KOSPI	Γ_2	SP500	IBOV	FTSE	KOSPI
SP500	1.000				SP500	1.000			
IBOV	0.754 (0.049)	1.000			IBOV	0.788 (0.072)	1.000		
FTSE	0.644 (0.061)	0.589 (0.048)	1.000		FTSE	0.675 (0.112)	0.583 (0.075)	1.000	
KOSPI	0.448 (0.051)	0.433 (0.058)	0.345 (0.086)	1.000	KOSPI	0.443 (0.117)	0.403 (0.146)	0.242 (0.164)	1.000

Γ_3	SP500	IBOV	FTSE	KOSPI
SP500	1.000			
IBOV	0.465 (0.096)	1.000		
FTSE	0.397 (0.062)	0.254 (0.095)	1.000	
KOSPI	0.301 (0.042)	0.200 (0.044)	0.191 (0.037)	1.000

more stable. A possible explanation for these results is that the switch between the calm and turbulent regimes occurs abruptly as seen in 'Two Regimes' section, 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.

Comparison of CCC and DCC models

In this section, we will elaborate a comparison of the econometric approach presented so far, the RSDC model, with the CCC model proposed by Bollerslev (1990) and the DCC model developed in Engle (2002). For the estimation of CCC and DCC, we used the routines provided by Kevin Sheppard in MFE Toolbox for MATLAB.[14] Furthermore, to establish a direct and fair comparison about the RSDC model's relative performance, we estimated versions of the RSDC model with conditional variances modelled only by the standard GARCH specification. Thus, we can check whether possible gains in terms of likelihood are not associated only with the introduction of the GJR model on the marginal distributions, as described in 'Marginal Distribution' section.

According to the analysis of estimates reported in Table 7, there is additional evidence of the issue raised in 'Marginal Distribution' section about the high persistence of the GARCH models in general. The sum of the calculated parameters for the DCC model reveals persistence very close to unity, as do the results of the univariate GARCH estimations. It should be mentioned again that this high persistence may be associated with no observed change in 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 used was as follows:

$$\overline{\Gamma}_t = (1 - a_1 - b_1)\Gamma + a_1(\tilde{U}_{t-1}\tilde{U}'_{t-1}) + b_1\overline{\Gamma}_{t-1} \tag{15}$$

$$\Gamma_t = D_t^{-1}\overline{\Gamma}_t D_t^{-1} \tag{16}$$

The correlation matrix $\overline{\Gamma}_t$ and the coefficients a_1 and b_1 from the DCC model are reported below.

After the estimation of the models (see Table 8), we created a comparative table (Table 9), summarizing the statistical performance of each approach to enrich the analysis. One of the first points to note is increase in the likelihood from the introduction of regime switch dynamics. As can be observed, the RSDC(2)-GJR-N (RSDC(2)-GJR-t) and RSDC(3)-GJR (RSDC(3)-GJR-t) models has −12794 (−12779) and −12763 (−12790) points, respectively, while the CCC and DCC models has −14484 and −14407 points, respectively.

The results of RSDC(2)-GARCH-N and RSDC(3)-GARCH-N, which incorporates only the GARCH model, serve to support the conclusion that the introduction of regime switching actually entails likelihood gains. Such models showed even

Table 8. Results for the CCC and DCC models.

Γ	SP500	IBOV	FTSE	KOPSI	DCC	a_1	b_1
SP500	1.000					0.0119 (0.0000)	0.9803 (0.0000)
IBOV	0.6595 (0.0001)	1.000					
FTSE	0.5734 (0.0002)	0.4831 (0.0002)	1.000				
KOPSI	0.4046 (0.0003)	0.3541 (0.0003)	0.2927 (0.0004)	1.000			

Table 9. Comparison of models.

	log L	Parameters	Observations	AIC[a]	SC[b]	HQ[c]
CCC[b]	− 14484	18	2531	11.460	11.501	11.475
DCC[b]	− 14407	20	2531	11.400	11.446	11.417
RSDC[b]-GJR-N[d]	− 12794	30	2531	10.134	10.203	10.159
RSDC[c]-GJR-N[d]	− 12763	40	2531	**10.117**	10.209	10.150
RSDC[b]-GJR-t[e]	− 12779	31	2531	10.122	**10.194**	**10.148**
RSDC[c]-GJR-t[5]	− 12790	41	2531	10.139	10.234	10.173

Notes: [a]Akaike information criterion.
[b]Schwarz information criterion.
[c]Hannan–Quinn information criterion.
[d]Normal distribution in the disturbances.
[e]t-Student distribution in the disturbances.

[14]Available at http://www.kevinsheppard.com/wiki/MFE_Toolbox. The functions ccc_mvgarch.m and dcc_mvgarch.m were used for the CCC and DCC models, respectively.

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 occurring at each instant of time was sufficiently high 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-*N* (RSDC-GJR-*t*) formulation with the CCC and DCC models.

After concluding that the application of RSDC-GJR models entails likelihood gains when compared with the CCC and DCC models, it is necessary to establish the appropriate number of regimes, that is a comparison between the specifications RSDC(2)-GJR and RSDC(3)-GJR. A possible selection criterion is the likelihood ratio, provided that the distribution of this test is 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 does not follow a standard distribution due to unidentified parameters under the null hypothesis.

Another alternative is to compare through information criteria. As proposed by Rydén (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 in Table 9. By the Schwartz and Hannan–Quinn information criteria, the model RSDC(2)-GJR-*t* is the best since it has the lowest value of these information criteria. When the AIC criterion is used, the model RSDC(3)-GJR-*N* is preferable. It is important to remember that RSDC-GARCH models are no longer considered.

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

VI. Conclusion

Given the main objective of this study, which was to analyse the phenomenon of financial contagion between stock market returns of different countries from an econometric perspective, we employed a methodology originally developed by Pelletier (2006), named RSDC model. A modification was made in the original RSDC model, the introduction of the GJR-GARCH-*N* and also GJR-GARCH-*t* models formulated in Glosten, Jagannathan, and Runkle (1993), on the equation of conditional univariate variances, thus allowing us to capture the asymmetric effects in volatility and heavy tails. Throughout the work, this methodology was applied to daily returns of SP500 (the United States), Bovespa Index (Brazil), FTSE100 (the United Kingdom) and KOSPI (Korea) from 1 February 2003 to 20 September 2012 and confronted with other models commonly used in literature.

The comparison of the results revealed that the adapted RSDC model presented gains in likelihood when compared with the CCC model proposed by Bollerslev (1990) and the DCC model developed in Engle (2002) for the series and sample period selected. The number of regimes for the adapted RSDC model was determined on the basis of information criteria, stability of regimes and degree of uncertainty about the definition of the regime at each instant of time. Thus, the RSDC(2)-GJR-*t* model with two regimes was defined as the most appropriate due to its overall better performance in general.

The results of the RSDC(2)-GJR-*t* 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 very restrictive definition of financial contagion by the World Bank, which says that contagion occurs when correlations between countries increase during periods of crisis with respect to correlations in calm periods, the results provide evidence for the existence of financial contagion between the markets of four countries studied. Such a conclusion should be evaluated with caution, since the nonuse of macroeconomic variables or economic fundamentals in the modelling process (mean equation) is a limitation to the chosen approach. As discussed in Section II, and taken as a premise, these factors or economic mechanisms would not be able to transmit the effects of the crises observed between 2003 and 2012 this quickly and abruptly.

The smoothed probabilities of each regime have relative stability and low uncertainty to determine the regime prevailing 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 behaviour throughout the sample. From 2003 to mid-2007, it is possible to observe a dominance of the regime categorized as calm (state 2). These long periods of low volatility are interrupted at some points by turbulence. One possible interpretation is that a turbulence shock in one country is transmitted to other markets, but when the intensity and direction are recognized, the correlation level falls as in a temporary financial shock. In contrast, from mid-2007 to 2012, the higher volatility state prevails in almost all observations, suggesting that financial crises during this period entailed permanent changes. In summary, the average duration of high volatility periods is greater in the second half of the sample.

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

Acknowledgements

Pedro L. Valls Pereira acknowledges the financial support from CNPq and FAPESP. We gratefully acknowledge two anonymous referees for suggestions and constructive comments that have led to improvement of the article. Of course, all errors are ours.

Disclosure statement

No potential conflict of interest was reported by the authors.

Funding

Financial support from CNPq and FAPESP was provided to Pedro L. Valls Pereira.

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