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Global financial crisis and emerging stock market contagion: A multivariate FIAPARCH–DCC approach

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ABSTRACT

This paper empirically investigates the contagion effects of the global financial crisis in a multivariate Fractionally Integrated Asymmetric Power ARCH (FIAPARCH) dynamic conditional correlation (DCC) framework during the period 1997–2012. We focus on five most important emerging equity markets, namely Brazil, Russia, India, China and South Africa (BRICS), as well as USA during different phases of the crisis. The length and the phases of the crisis are identified based on both an economic and a statistical approach. The empirical evidence does not confirm a contagion effect for most BRICS during the early stages of the crisis, indicating signs of isolation or decoupling. However, linkages reemerged (recoupled) after the Lehman Brothers collapse, suggesting a shift on investors' risk appetite. Moreover, correlations among all BRICS and USA are increased from early 2009 onwards, implying that their dependence is larger in bullish than in bearish markets. These findings do not show a pattern of contagion for all BRICSs' markets that could be attributed to their common trade and financial characteristics and provide important implications for international investors and policymakers.

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1. Introduction

The extent of recent Global Financial Crisis (GFC, hereafter) and the severe damaging consequences of being affected by contagion, characterized it as the worst financial crisis since the Great Depression of 1929. During crises, the issues of risk management and asset allocation are very important to practitioners and academics. So the impact and the transmission of shocks among financial markets is a crucial research area.

There is a large body of literature on what the term "contagion" entails and on the channels of contagion. Some researchers argue that there are "fundamental" reasons for a significant increase in cross-market linkages after a shock to one country, while others refer to "pure" contagion which cannot be explained by changes in fundamentals. Pure contagion is specified as a significant increase in cross-market correlations after a shock and relates to shifts in investors' appetite for or aversion to risk. When investors' appetite for risk falls, they immediately reduce their exposure to risky assets and consequently fall in value together. When investors' appetite for risk rises, demand for risky assets is increasing and their value rises simultaneously. Therefore, this type of contagion runs along the lines of risk and ignores fundamentals, trade and exchange rate arrangements (Kumar & Persaud, 2001).[1]

This paper investigates the existence of a "pure" contagion mechanism among the source of the GFC (USA) and five of the most important emerging equity markets, namely Brazil, Russia, India, China and South Africa (BRICS), from 31st January 1997 to 1st February 2012. To capture the contagion behavior over time, we estimate time-varying dynamic conditional correlations (DCCs) among USA and BRICS into an autoregressive (AR(1))-Fractionally Integrated Asymmetric

[1] The contagion literature summarizes several types of transmission channels: the correlated information channel or the wake-up call hypothesis, the liquidity channel, the cross-market hedging channel and the wealth effect channel (see Chiang, Jeon, & Li, 2007; Pericoli & Sbracia, 2003 for a survey of the literature on each contagion channel). Although testing directly for a specific contagion channel may be more useful, many difficulties (e.g., the lack of availability of consistent financial and microstructure data and prior identification of the relevant fundamental variables) exacerbate problems related to the implementation. Thus, most of the recent papers focus on the investigation of asset-return co-movements, using various types of correlation analyses. Following these studies, we define financial contagion as a significant increase in correlation between stock returns in different markets.

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Power ARCH (FIAPARCH) framework, and then test their statistical significance during several phases of the GFC.[2] The FIAPARCH model increases the flexibility of the conditional variance specification by allowing an asymmetric response of volatility to positive and negative shocks and long-range volatility dependence. At the same time, this model allows the data to determine the power of returns for which the predictable structure in the volatility pattern is the strongest (Conrad, Karanasos, & Zeng, 2011).[3] To identify the crisis period and its phases, we use both official data sources for all key financial and economic events representing the GFC (Bank for International Settlements, 2009; Federal Reserve Bank of Saint Louis, 2009), and regimes of excess stock market volatility estimated by a Markov Switching Dynamic Regression (MS-DR, hereafter) model.

Although there is an extensive literature on financial contagion during several crises of the 1980s and 1990s (see Kaminsky, Reinhardt, & Vegh, 2003, for a survey), the research on GFC is still growing. Dooley and Hutchison (2009) provide evidence on the decoupling of emerging CDS markets from early 2007 to summer 2008, while thereafter responded very strongly to the deteriorating situation in the USA financial system and real economy. Samarakoon (2011) shows evidence of contagion among USA and frontier equity markets, but not among USA and emerging markets by constructing various shock models. Using a DCC–GARCH model, Syllignakis and Kouretas (2011) capture contagion effects among US and German stock markets and seven emerging Central and Eastern Europe markets. However, studies that focus specifically on BRICSs' markets are rare. Aloui, Aissa, and Nguyen (2011) show strong evidence of dependence between BRICSs' stock markets and USA, using copulas functions. Kenourgios and Padhi (2012) provide evidence on contagion of the subprime crisis of 2007, among other crises, using an asymmetric generalized dynamic conditional correlation model (AG–DCC) for both equity and bond markets of emerging economies around the world.[4]

This paper contributes to the existent literature in the following aspects. Firstly, we examine separately the contagion effects during different phases of the GFC. Other studies do not take into account different periods of the crisis. As recent studies provide evidence on the insulation of emerging markets from the US subprime crisis (e.g., Dooley & Hutchison, 2009), our empirical analysis allows us to test the decoupling–recoupling hypothesis, which supports that some markets show immunity during different phases of a crisis or even the entire crisis period. Secondly, we capture the time-varying DCCs from a multivariate AR(1)–FIAPARCH–DCC model, which goes beyond a simple analysis of correlation taking into account long memory behavior, speed of market information, asymmetries and leverage effects. Thirdly, we provide further evidence of contagion effects on BRICS, which their relative importance as an engine of new demand growth and spending power seems to shift more dramatically and quickly than expected.

The results provide evidence on the decoupling hypothesis for most of the BRICSs' markets at the early stages of the crisis, while a contagion effect (recoupling) exists for almost all of them after the Lehmann Brothers collapse, implying the existence of a shift on investors' risk appetite. Moreover, conditional correlations between BRICS and USA are all positive and statistically significant from early 2009 onwards (post-crisis period), implying that the crisis accelerates the integration process of BRICS and their dependence with USA is larger in bullish markets.

The structure of the paper is organized as follows. Section 2 presents the multivariate AR(1)–FIAPARCH–DCC model and the identification of the crisis period based on an economic and a statistical approach. Section 3 provides the data and a preliminary analysis. The empirical results and their interpretation are displayed and discussed in Section 4, while Section 5 reports the summary and concluding remarks.

2. Methodology framework

2.1. Multivariate AR(1)–FIAPARCH–DCC process

The multivariate DCC model proposed by Tse and Tsui (2002) involves two stages to estimate the conditional covariance matrix H_t. In the first stage, a univariate FIAPARCH (1,d,1) model is fitted for each of the stock market returns in order to obtain the estimations of $\sqrt{h_{ii,t}}$. We assume that daily stock returns are generated by an autoregressive AR(1) process of the following form:

$$(1-kL)r_t = \mu + \varepsilon_t, \quad t \in \mathbb{N} \tag{1}$$

with

$$\varepsilon_t = e_t\sqrt{h_t}$$

where $\mu \in [0,\infty)$, $|k| < 1$ and $\{e_t\}$ are independently and identically distributed (i.i.d.) random variables and h_t is positive with probability one. The AR(1) term captures the speed that market information is reflected in stock prices.

The FIAPARCH model suggested by Tse (1998) as an extension of the simple GARCH model is given by the following expression:

$$(1-\lambda L)\left(h_t^{\delta/2}-c\right) = \left[(1-\lambda L)-(1-\xi L)(1-L)^d\right](1+\gamma s_t)|\varepsilon_t|^\delta \tag{2}$$

where $c \in (0,\infty)$, $|\lambda| < 1$, $|\xi| < 1$, $0 \le d \le 1$, $s_t = 1$ if $\varepsilon_t < 0$ and 0 otherwise, the power term parameter δ ($\delta > 0$) is a Box–Cox transformation of h_t, γ is the leverage coefficient, while $(1–L)^d$ is the financial differencing operator expressed in terms of a hypergeometric function (see Conrad, Karanasos, & Zeng, 2008, for the expression of this function). When $\gamma > 0$, negative shocks have more impact on volatility than positive shocks. The advantage of this class of models is its flexibility since it includes a large number of alternative GARCH specifications (see Conrad et al., 2011 for an application of this model to national stock market returns).

In the second stage, conditional correlation is estimated using the transformed stock-return residuals. Transformed stock return residuals are estimated by their standard deviations from the first stage. So, we specify the multivariate conditional variance as:

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

where $D_t = diag(h_{11t}^{1/2} \ldots\ldots h_{NNt}^{1/2})$, h_{iit} is defined as the conditional variance obtained from the univariate AR(1)–FIAPARCH (1,d,1) model, and $R_t = (1-\theta_1-\theta_2)R + \theta_1\psi_{t-1} + \theta_2 R_{t-1}$.[5] Furthermore, θ_1 and θ_2 are the non-negative parameters satisfying $\theta_1 + \theta_2 < 1$, $R = \{\rho_{ij}\}$ is a time-invariant symmetric $N \times N$ positive definite parameter matrix

[2] For a review of conventional methodologies (e.g., cointegration and vector error correction models, models of interdependence, autoregressive conditional heteroskedasticity-ARCH specifications, principle components, spillover models and the correlation breakdown analysis) used in the empirical analysis of contagion, see Dungey, Fry, González-Hermosillo, and Martin (2005). For a review of other more advanced techniques, which avoid the restrictions of the conventional approaches (e.g., regime switching models and copulas with and without regime-switching), see Kenourgios and Padhi (2012).

[3] Although many studies use various multivariate GARCH models in order to estimate DCCs among markets during financial crises (e.g., Celic, 2012; Chiang et al., 2007; Kenourgios, Samitas, & Paltalidis, 2011), the forecasting superiority of FIAPARCH on other GARCH models is supported by Conrad et al. (2011) and Chkili, Aloui, and Ngugen (2012).

[4] Other studies investigate contagion focusing on different asset classes (e.g., commodities, energy, real estate, etc.) during the GFC (see for example Chan, Treepongkaruna, Brooks, & Gray, 2011).

[5] Engle (2002) presents a different form of DCC model. The evolution of the correlation in DCC is given by: $Q_t = (1-\alpha-\beta)\overline{Q} + \alpha u_{t-1} + \beta Q_{t-1}$, where $Q_t = (q_{ij,t})$ is the $n \times n$ time-varying covariance matrix of u_t, $\overline{Q} = E[u_t u'_t]$ is the $n \times n$ unconditional variance matrix of u_t, while α and β are nonnegative parameters satisfying $(\alpha + \beta) < 1$. Since Q_t does not generally have unites on the diagonal, the correlation matrix R_t is obtained by scaling Q_t as follows: $R_t = (diag(Q_t))^{-1/2}Q_t(diag(Q_t))^{-1/2}$.

with $\rho_{ii} = 1$ and ψ_{t-1} is the $N \times N$ correlation matrix of ε_τ, for $\tau = t - M, t - M + 1, \ldots, t - 1$). Its $i, j - th$ element is given by:

$$\psi_{ij,t-1} = \frac{\sum_{m=1}^{M} u_{i,t-m} u_{j,t-m}}{\sqrt{\left(\sum_{m=1}^{M} u_{i,t-m}^2\right)\left(\sum_{h=1}^{M} u_{j,t-m}^2\right)}}, 1 \le i < j \le N \tag{4}$$

where $u_{i,t} = \varepsilon_{i,t} / \sqrt{h_{ii,t}}$ is the transformed by their estimated standard deviations stock-return residuals taken from the univariate AR(1)–FIAPARCH (1,d,1). The matrix ψ_{t-1} can be expressed as $\psi_{t-1} = B_{t-1}^{-1} L_{t-1} L_{t-1}^{'} B_{t-1}^{-1}$, where B_{t-1} is a $N \times N$ diagonal matrix with $i - th$ diagonal element given by $\left(\sum_{h=1}^{M} u_{i,t-h^2}\right)^{1/2}$ and $L_{t-1} = (u_{t-1}, \ldots, u_{t-M})$ is a $N \times N$ matrix, with $u_t = (u_{1t}, u_{2t}, \ldots, u_{Nt})'$.

A necessary condition to ensure the positivity of ψ_{t-1} and therefore of R_t is that $M \ge N$. Then, R_t itself is a correlation matrix if R_{t-1} is also a correlation matrix. The correlation coefficient in a bivariate case is expressed as follows:

$$\rho_{12,t} = (1-\theta_1-\theta_2)\rho_{12} + \theta_2 \rho_{12,t} + \theta_1 \frac{\sum_{m=1}^{M} u_{1,t-m} u_{2,t-m}}{\sqrt{\left(\sum_{m=1}^{M} u_{1,t-m}^2\right)\left(\sum_{h=1}^{M} u_{2,t-m}^2\right)}}. \tag{5}$$

2.2. Crisis period specification

The recent GFC has some unique characteristics, such as the length, breadth and crisis sources. Compared to other financial crises (e.g., 1997 Asian crisis and 2001 internet bubble crisis), many researchers determine the crisis length and source ad-hoc based on major economic and financial events (e.g., Forbes & Rigobon, 2002). On the other hand, many studies use Markov regime switching models to identify the crisis period endogenously (e.g., Boyer, Kumagai, & Yuan, 2006). It is worth to mention that in order to define correctly the crisis period, studies on financial contagion are in some degree arbitrary. Even studies that avoid discretion in the definition of the crisis period use discretion in the choice of the econometric model to estimate the location of the crisis period in time (Baur, 2012).[6]

We specify the length of GFC and its phases following both an economic and a statistical approach as follows. Firstly, we define a relatively long crisis period based on all major international financial and economic news events representing the GFC. The choice of the crisis period is based on official timelines provided by Federal Reserve Board of St. Louis (2009) and the Bank for International Settlements (BIS, 2009), among others. These studies separate the timeline of GFC in four phases. Phase 1 described as "initial financial turmoil" spans from 1st August 2007 to 15th September 2008. Phase 2 is defined as "sharp financial market deterioration" (16th September 2008 until 31st December 2008), phase 3 described as "macroeconomic deterioration" (1st January 2009 until 31st March 2009) and phase 4 is a phase of "stabilization and tentative signs of recovery" (post-crisis period) including a financial market rally (1st April 2009 onwards, until the end of the sample period). Therefore, the crisis can be defined from August 2007 until March 2009 covering the first three phases.

Secondly, we identify regimes of excess stock market conditional volatility ($h_{i,t}$) via a Markov Switching Dynamic Regression (MS-DR) model, which takes into account endogenous structural breaks and thus allows the data to determine the beginning and end of each phase of the crisis. In our estimation, MS-DR model assumes the existence of two regimes ("stable" and "volatile"), where the regime 0 ("stable" regime) defines the lower values of $h_{i,t}$ and the regime 1 ("volatile regime") the higher values. BRICSs' conditional volatilities are obtained from the AR(1)–FIAPARCH model during the full sample period. The smoothed regime probabilities of $h_{i,t}$ depicted in Fig. 1 reveal that that the "volatile"/crisis regimes for each examined market are all located within the crisis period based on economic and financial news events described above.

However, the phases as identified by the economic approach are treated as distinct and independent and thus the analysis of contagion does not take into account the lagged impact of the crisis on each of the BRICSs' markets. To overcome this problem, the estimated regimes of excess volatility are used to identify the start date and the end date of the crisis, as well as the different phases of the crisis for each market which are treated as overlapping. In other words, this statistical approach indicates the crisis period and the phases endogenously when each market hitted hardest by the GFC. Table 1 presents the start and the end dates of the crisis periods for each market based on regimes of excess volatility during the period from August 2007 until the end of the sample (1st February 2012). Regimes 1a and 1b represent the crisis periods when each market exhibits high persistence of excess volatility (smoothed regime prob. near one), while all other periods are identified as stable periods with no excess volatility (Regime 0).

3. Data and preliminary analyses

The data comprises daily Morgan Stanley Capital Index (MSCI) aggregate prices for US and BRICSs' stock markets sourced from Datastream database during a period from 31st January 1997 until 1st February 2012, leading to a sample size of 3913 observations. For each national MSCI index, the continuously compounded return is estimated as $r_t = 100[\log(p_t) - \log(p_{t-1})]$, where p_t is the price on day t.[7]

Summary statistics for BRICSs' and US stock returns are displayed in Table 2 (Panel A). All stock market returns, except for China, are skewed to the left. Also, all market returns exhibit excess kurtosis (fat tails). In order to accommodate the presence of leptokurtosis, we assume student-t distributed innovations. Furthermore, the Jarque–Bera statistic rejects normality at the 1% level for all indices. Moreover, all return series are stationary, I(0), suitable for long memory tests and exhibit ARCH effects (results not reported here). Finally, all unconditional correlations are statistically significant, with the higher value (0.5497) between Brazil and USA and the lower one (0.1350) between China and USA. In order to detect long-memory process in our time series, we implement several long-memory tests on two proxies of volatility: a) squared returns and b) absolute returns.[8] Based on these tests' results displayed in Table 2 (Panel B), we conclude that there is a long-range memory process for all examined markets, while all volatility proxies seem to be governed by a fractionally integrated process. Overall, these results support that FIAPARCH is an appropriate specification to capture volatility clustering, asymmetries and long-range memory characteristics.

Fig. 2 illustrates the evolution of USA and BRICSs' stock indices during the period from 31st January 1997 until 1st February 2012. The figure shows strong co-movements among all BRICS and USA and significant declines in the levels during 2008, especially at the time of Lehman Brothers collapse (15th September 2008). Fig. 3 illustrates the evolution of stock market returns over time. The figure shows that all markets trembled since 2008.[9] Stock markets show

[6] Baur (2012) uses both key financial/economic events and estimates of excess volatility to identify the crisis period and investigates the spread of the GFC from the financial sector to real economy.

[7] All MSCI are denominated in USD. As suggested by Bekaert and Harvey (1995), this procedure eliminates the local inflation.

[8] These are the log-periodogram regression (GPH) test of Geweke and Porter-Hudak (1983), the Gaussian semi parametric (GSP) test of Robinson (1995) and the rescaled range (R/S) test of Lo (1991).

[9] Several other crises occurred during the sample period (e.g., Asian crisis in 1997, Russia's rouble devaluation in 1998, and Brazilian real devaluation in 1999). These crises partially explain the increased volatility of stock returns during the period 1997–2000.

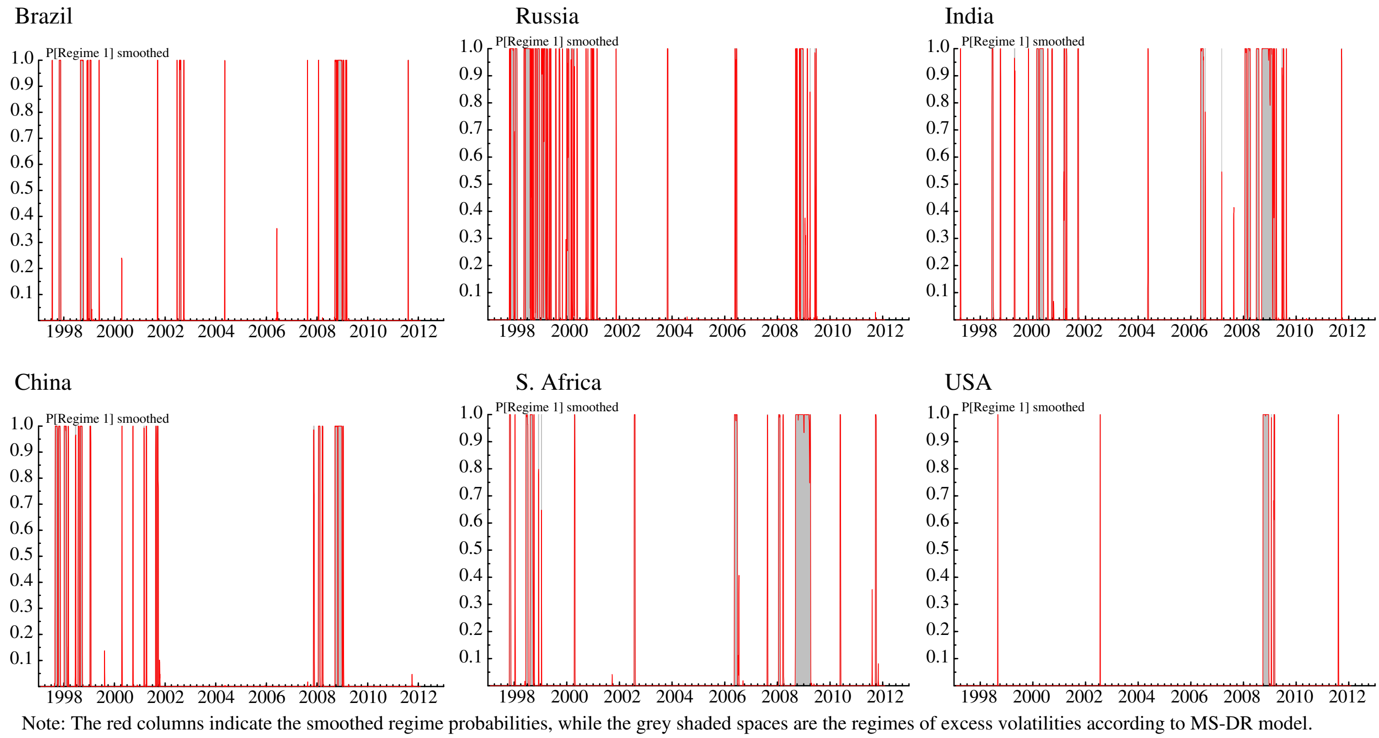

Fig. 1. Regime classification of stock markets' conditional volatilities (h_t).

volatility clustering, revealing the presence of heteroskedasticity. This characteristic supports the use of GARCH family models to analyze stock returns dynamics.

4. Empirical results

4.1. The bivariate AR(1)–FIAPARCH(1,d,1)–DCC estimates

We proceed with the estimation of the bivariate AR(1)–FIAPARCH (1,d,1)–DCC model among USA and BRICS. Estimation results are reported in Table 3 (Panel A). The bivariate specification of the above model is chosen according to likelihood ratio tests and the minimum value of the information criteria, while the lag order (1,d,1) is selected by Akaike (AIC) and Schwarz (SIC) information criteria (the results are not reported). The AR(1) term is positive for all emerging markets due to partial adjustment, indicating that relevant market information is rapidly reflected in stock prices. In addition, the coefficient γ, which measures the leverage effect, is highly significant and positive for all stock markets, indicating volatility clustering and leverage effects. Moreover, all stock markets display highly significant differencing fractional parameters (d), indicating a high degree of persistence behavior. This implies that the impact of shocks on the conditional volatility of stock market returns consistently exhibits a hyperbolic rate of decay.

Estimates of the DCC model are presented in Table 3 (Panel B). ARCH and GARCH parameters (alpha and beta) are statistically significant and non-negative, justifying the appropriateness of the FIAPARCH (1,d,1) specification. Average conditional correlation is higher among USA and Brazil and lower among USA and India during the full sample period. Furthermore, the t-student degrees of freedom parameter (df) is highly significant for all stock markets. This result confirms our preliminary analysis and subsequently the choice of the t-student as an appropriate distribution. According to Hosking (1980) and McLeod and Li (1983) autocorrelation test results presented in Table 3 (Panel C), we accept the null hypothesis of no serial correlation and thus there is no evidence of statistical misspecification.

We also estimate a regression equation for the DCCs on a constant and a trend in order to examine whether the conditional correlations changed over time. Table 4 reports the regression results, which show a statistically significant rise in all conditional correlations during the entire sample period. The rise in DCCs is measured by the term $\Delta\rho$, which is equal to the difference between the last and first fitted values. The increase in DCCs is particularly evident among USA–South Africa ($\Delta\rho = 89.37\%$) and USA–Brazil ($\Delta\rho = 43.76\%$), suggesting that these markets have become more interrelated over the examined period. However, the increase in DCCs among USA and the rest of the emerging markets is relatively low (between 1.54% and 11.71%). Fig. 4 illustrates the evolution of the estimated dynamic conditional correlations dynamics among USA and BRICS. A common characteristic is the increasing trend of all DCCs with different intensities over time. The

Table 1
GFC periods based on regimes of excess volatility.

	Crisis regime 1a		Crisis regime 1b	
	Starting date	Ending date	Starting date	Ending date
Brazil	15th Sep. 2008	25th Dec. 2008	7th Jan. 2009	23rd Feb. 2009
Russia	24th Sep. 2008	26th Dec. 2008	17th Feb. 2009	31st Mar. 2009
India	21st Jan. 2008	4th Aug. 2008	15th Sep. 2008	10th Mar. 2009
China	12st Nov. 2007	26th Mar. 2008	16th Sep. 2008	16th Jan. 2009
S. Africa	16st Jan. 2008	25th Mar. 2008	18th Sep. 2008	7th Apr. 2009

Note: Smoothed probabilities of regimes are estimated via an MS-DR model during the full sample period. The identification of the crisis periods for each market (regimes 1a and 1b) is based on high persistence of excess volatility (smoothed regime prob. near 1) during the period from August 2007 until the end of the sample (1st February 2012). Regimes with low persistence of excess volatility (i.e. below one week) are ignored.

Table 2
Descriptive statistics and long-memory tests' results.

	Brazil	Russia	India	China	South Africa	USA
Panel A: descriptive statistics						
Mean	0.0146	0.0130	0.0143	0.0007	0.0108	0.0057
Std. deviation	1.0561	1.3428	0.7793	0.9340	0.8024	0.5751
Skewness	−0.2744***	−0.4490***	−0.2903***	0.0039***	−0.4157***	−0.218***
t-Statistic	7.01	11.47	7.41	3.15	−10.60	−5.57
Kurtosis	6.3773***	11.612***	3.9068***	4.8849***	5.0900***	7.1299***
t-Statistic	81.48	148.37	37.14	62.41	−65.06	−91.09
Jarque–Bera	6680.10***	22116.00***	1432.60***	3890.50***	4340.90***	8319.40***
p-Value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Unconditional correlations (BRICS vs USA)	0.5497***	0.2680***	0.1761***	0.1359***	0.3123***	–
t-Statistic	41.1547	17.3981	11.1889	8.5811	20.5637	–
Panel B: long-memory tests						
GPH test — d estimates						
Absolute returns $\|r\|$						
$m = T^{0.5}$	0.3950***	0.5685***	0.3550***	0.5421***	0.5709***	0.4846***
p-Value	0.0000	0.0001	0.0000	0.0000	0.0000	0.0000
$m = T^{0.6}$	0.4129***	0.4830***	0.4514***	0.4356***	0.4825***	0.5599***
p-Value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Squared returns r^2						
$m = T^{0.5}$	0.3269***	0.4163***	0.3208***	0.4757***	0.4796***	0.4877***
p-Value	0.0003	0.0000	0.0004	0.0000	0.0000	0.0000
$m = T^{0.5}$	0.4322***	0.4544***	0.4363***	0.3855***	0.5142***	0.5648***
p-Value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
GSP test — d estimates						
Absolute returns $\|r\|$						
$m = T/4$	0.2920***	0.2667***	0.2536***	0.2656***	0.2784***	0.2852***
p-Value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
$m = T/16$	0.4654***	0.4427***	0.397***	0.3913***	0.4374***	0.5604***
p-Value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Squared returns r^2						
$m = T/4$	0.2984***	0.2058***	0.2420***	0.2754***	0.2322***	0.2862***
p-Value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
$m = T/16$	0.5102***	0.3800***	0.3592***	0.3570***	0.4580***	0.5968***
p-Value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Rescaled range (R/S) — test statistics						
Absolute returns $\|r\|$						
Number of autocorrelations = 5, RV stat.	1.9771***	2.2141***	1.8125***	1.9398***	1.9256***	1.9794***
p-Value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Number of autocorrelations = 10, RV stat.	3.1613***	3.5099***	2.8031***	2.9938***	3.0128***	3.3289***
p-Value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Squared returns r^2						
Number of autocorrelations = 5, RV stat.	2.0100***	1.9133***	1.8281***	1.9812***	1.8511***	1.9835***
p-Value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Number of autocorrelations = 10, RV stat.	3.3285***	2.6431***	2.8110***	2.9082***	2.8742***	3.3167***
p-Value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Notes: Stock returns are in daily frequency. r^2 and $|r|$ are squared log return and absolute log return, respectively. (m) denotes the bandwidth for the Geweke and Porter-Hudak's (1983) (GPH) test and the Gaussian semi parametric (GSP) test of Robinson (1995). According to the GSP and GPH tests' results, the null hypothesis of no long memory is rejected at the 1% level for absolute and squared returns. According to (R/S) tests' results, the null hypothesis of no long term dependence is rejected since the p-value is less than the significance level.
***, ** and * denote statistical significance at 1%, 5% and 10% levels, respectively.

above findings motivate a more extensive analysis of DCCs, in order to capture contagion dynamics during different phases of the GFC.

4.2. The DCC behavior during different periods of the GFC

We next provide further results on the contagion effects during different phases of the GFC. Using various dummy variables allows us to identify which of the subperiods exhibit contagion effects for the BRICSs' emerging markets. We create dummies, which are equal to unity for the corresponding phase of crisis and zero otherwise, to the following mean equation in order to describe the behavior of DCCs over time:

$$\rho_{ij,t} = c_0 + \sum_{p=1}^{P} \psi_\rho \rho_{ij,t-p} + \sum_{k=1}^{\lambda} \beta_k dummy_{k,t} + \eta_{ij,t} \tag{6}$$

where c_0 is a constant term, $\rho_{ij,t}$ is the pairwise conditional correlation between the stock returns of BRICS and the stock returns of USA, such that i corresponds to USA while j corresponds to Brazil, Russia, India, China and S. Africa, and $k = 1 \ldots \lambda$ are the number of dummy variables corresponding to different periods of the GFC, which are identified based on an economic and a statistical approach. Based on the economic approach, $dummy_{k,t}$ (k = 1,2,3) corresponds to the first three phases of the crisis, while the fourth dummy (k = 4) to the phase of "stabilization and recovery" (post-crisis period). Following the statistical approach, the first two dummies (k = 1,2) correspond to the two crisis regimes (1a and 1b) presented in Table 1, while the third dummy to the post-crisis regime (from the end of crisis regime 1b onwards).

Furthermore, the conditional variance equation is assumed to follow an asymmetric GARCH (1,1) specification of Glosten, Jagannathan, and

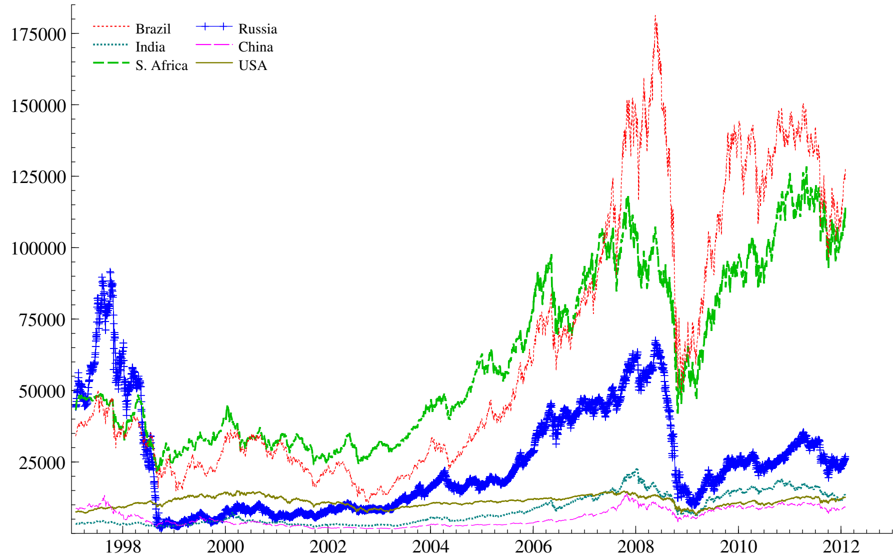

Fig. 2. MSCI stock index behavior over time.

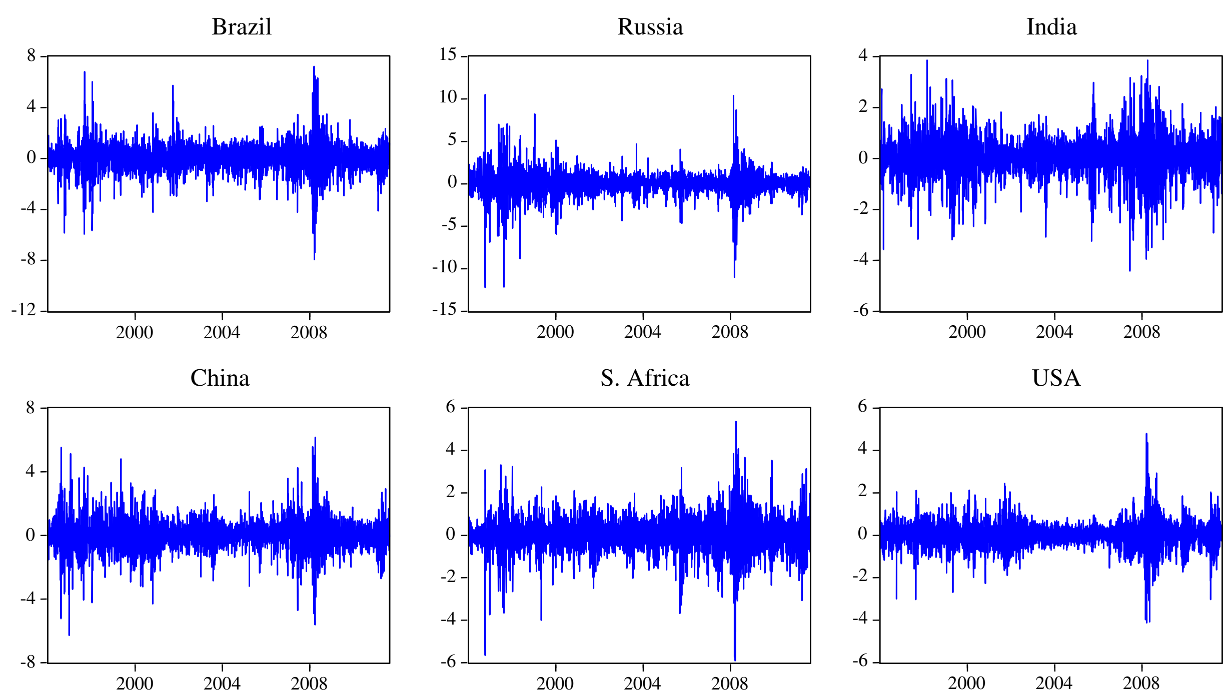

Fig. 3. The MSCI stock return behavior over time.

Runkle (1993) including the dummy variables identified by the two approaches[10]:

$$h_{ij,t} = \alpha_0 + \alpha_1 h_{ij,t-1} + \sum_{k=1}^{\lambda} \zeta_k dummy_{k,t} + v_1 \eta^2_{ij,t-1} + \alpha_2 \eta^2_{ij,t-1} I\left(\eta_{ij,t-1}<0\right) \tag{7}$$

As the model implies, the significance of the estimated dummy coefficients indicates structural changes in mean or/and variance shifts of the correlation coefficients due to external shocks during the different periods of the GFC. Specifically, a positive and statistically significant dummy coefficient in the mean equation indicates that the correlation during a specific period of the crisis is significantly different from that of the previous phase, supporting a contagion effect. Otherwise, BRICS are insulated and the decoupling hypothesis holds.

[10] This model is selected because all DCCs exhibit asymmetries and strong ARCH effects. The results are not presented here but are available upon request.

Table 3
Estimation results of the bivariate AR(1)–FIAPARCH(1,d,1)–DCC model.

	USA–Brazil		USA–Russia		USA–India		USA–China		USA–South Africa	
	USA	Brazil	USA	Russia	USA	India	USA	China	USA	S. Africa
Panel A: estimates of AR(1)–FIAPARCH model										
Const. (M)	0.0001	0.0119	0.0001	0.0320**	0.0001	0.0348***	0.0001	0.0152**	0.0001	0.0227**
t-Stat.	0.0234	0.7528	0.0234	2.120	0.0234	2.995	0.234	2.112	0.0234	2.099
AR(1)	−0.0338**	0.1282***	−0.0338**	0.0726***	−0.0338**	0.0967***	−0.0338**	0.1029***	−0.3388**	0.0913***
t-Stat.	−2.081	7.321	−2.081	4.144	−2.081	5.422	−2.233	6.124	−2.081	5.452
Const. (V)	0.6424***	0.7772***	0.6424***	2.6033***	0.6424***	1.0564***	0.6425***	0.9055***	0.6424***	0.2385**
t-Stat.	4.897	4.461	4.897	2.868	4.897	8.876	4.897	2.808	4.897	2.488
d-Figarch	0.3431***	0.2319***	0.3431***	0.4433***	0.3431***	0.3647***	0.3431***	0.3713***	0.3431***	0.2488***
t-Stat.	9.314	7.312	9.314	9.351	9.314	8.876	9.348	7.909	9.314	5.977
ARCH	0.2022***	0.0230	0.2022***	0.104	0.2022***	0.1825***	0.2020***	0.2530***	0.2022***	0.1431
t-Stat.	2.922	0.1922	2.922	1.198	2.922	3.189	2.945	3.536	2.922	0.1031
GARCH	0.4916***	0.1763	0.4916***	0.4016***	0.4916***	0.4363***	0.4913***	0.4995***	0.4916***	0.3204***
t-Stat.	5.434	1.326	5.434	3.896	5.434	6.834	5.470	5.331	5.434	3.117
APARCH (γ)	0.9993***	0.8331***	0.9993***	0.2378***	0.9993***	0.4175***	0.9993***	0.2983***	0.9993***	0.5778***
t-Stat.	296.5	5.333	296.5	4.198	296.5	5.014	291.1	4.722	296.5	2.761
APARCH (δ)	1.2539***	1.4174***	1.2539***	1.7912***	1.2539***	1.5759***	1.2543***	1.8060***	1.2539***	1.7129***
t-Stat.	29.97	14.78	29.97	15.55	29.97	14.12	35.19	16.61	29.97	9.89
Panel B: estimates of DCC model										
Average CORij	0.5427		0.2732		0.0906		0.1218		0.2874	
Alpha	0.0183***		0.0122***		0.0037***		0.0040*		0.0105**	
t-Stat.	4.442		3.764		5.045		1.654		2.342	
Beta	0.9742***		0.9848***		0.9962***		0.9940***		0.9869***	
t-Stat.	170.3		245.9		1188		223.60		168.8	
df	8.7540***		6.9177***		8.9221***		7.892***		9.8084***	
t-Stat.	11.55		15.00		11.35		9.35		11.82	
Panel C: diagnostic tests										
Hosking (50)	27.431		212.667		48.688		92.328		25.673	
p-Value	0.1235		0.2566		0.9977		0.9999		0.9616	
Hosking^2 (50)	4.415		45.095		4.273		9.932		2.355	
p-Value	0.9995		0.9995		0.9999		0.9999		0.9999	
Li–McLeod (50)	27.382		215.660		49.518		99.130		25.885	
p-Value	0.1248		0.2128		0.9970		0.9999		0.9588	
McLeod-Li^2 (50)	4.528		55.928		6.182		21.520		2.847	
p-Value	0.9994		0.9994		0.9999		0.9999		0.9999	

Notes: The bivariate specification and optimal lags of the model are chosen according to likelihood ratio tests and Akaike (AIC) and Schwarz (SIC) information criteria, respectively. Power terms (δ) of returns are statistically significant (ranging from 1.2543 to 1.8060), supporting the selection of FIAPARCH model. Average CORij is the average dynamic conditional correlation between USA (stock market i) and each of BRICS (markets j). Student-df is student's distribution's degrees of freedom. Hosking (1980) and McLeod and Li (1983) multivariate Portmanteau statistics do not reject the null hypothesis of no serial correlation (using 50 lags).
***, ** and * denote statistical significance at 1%, 5% and 10% levels, respectively.

Table 5 presents the estimates of the mean and variance equations, setting a dummy variable for each phase of the crisis according to the economic approach. For the mean equation, dummy coefficient $\beta_{1,t}$ is positive and significantly different from that of the pre-crisis period (stable) only for Russia and India during the first phase of the crisis ("initial financial turmoil"), supporting the existence of contagion effects. At the next phase of "sharp financial market deterioration", Russia's dummy coefficient $\beta_{2,t}$ is statistically insignificant, implying a decoupling from the crisis, while the Brazilian and Chinese markets recoupled. The South African market is still insulated (decoupled) from the GFC, while contagion is present for the Indian market as in previous phase. During the third phase of "macroeconomic deterioration", decoupling is present only for the Brazilian market (i.e., insignificant $\beta_{3,t}$ coefficient), Russia and South Africa recoupled, while a contagion effect exists for the Indian market. Finally, all BRICSs' dummy coefficients ($\beta_{4,t}$) are positive and statistically significant at the fourth phase of "stabilization and signs of recovery" (post-crisis period), supporting their increasing dependence with USA.

Table 6 reports the estimating results using three dummy variables for the periods identified by regimes of excess volatility (statistical approach). The first major difference from the results of Table 5 is observed on the initial stages of the GFC, since contagion effects in BRICS started to appear after the collapse of Lehmann Brothers (15th September 2008). This finding indicates that the impact of the

Table 4
DCC statistics for the full sample period.

	USA–Brazil	USA–Russia	USA–India	USA–China	USA–S. Africa
Constant	0.4453***	0.1539***	−0.0186***	0.0485***	0.1986***
t-Statistic	153.26	52.0488	−13.2888	39.9201	77.5659
Trend (*1000)	0.0498***	0.0610***	0.0559***	0.0375***	0.0454***
t-Statistic	38.7237	46.54	90.0903	69.6064	40.0011
Δρ%	43.76%	1.54%	11.75%	3.02%	89.37%

Notes: Trend is the slope coefficient of a regression of DCCs, on a constant and a time trend. The rise of DCCs is measured by Δρ which is equal to the difference between the last and first fitted values of a regression of DCCs on a constant and a zero-mean time trend.
***, ** and * denote statistical significance at 1%, 5% and 10% levels, respectively.

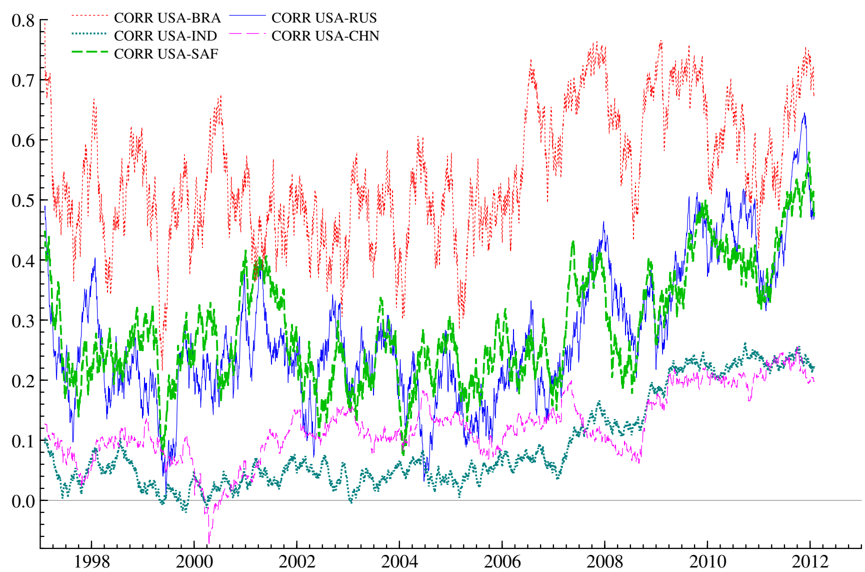

Fig. 4. The DCC behavior over time.

crisis on each emerging market has been lagged. Specifically, a contagion effect exists from 15th September 2008 until 25th December 2008 (crisis regime 1a) for Brazil, from 17th February 2009 until 31st March 2009 (crisis regime 1b) for Russia, from 16th September 2008 until 16th January 2009 (crisis regime 1b) for China and from 18th September 2008 until 7th April 2009 (crisis regime 1b) for South Africa. The only exemption is India, which seems to be affected from 21st January 2008 until 4th August 2008 (before the Lehman Brothers event — crisis regime 1a) and from 15th September 2008 until 10th March 2009 (crisis regime 1b).

The other two differences are observed for Russia and South Africa. In contrary to the results based on the economic approach,

Table 5
Tests of changes in dynamic correlations between market stock returns during the phases of GFC (economic approach).

Mean Eq.	USA–BRA	USA–RUS	USA–IND	USA–CHN	USA–SAF
c_0	0.0056***	0.0027***	0.0003***	0.0765***	0.0027***
z-Stat.	3.4568	6.8068	3.9136	3.2361	6.8180
ψ_1	0.9903***	0.9897***	0.9920***	0.9923***	0.9915***
z-Stat.	293.120	565.697	550.25	474.429	644.552
β_1	0.0010	0.0013***	0.0007***	−0.0002	0.0003
z-Stat.	1.2142	2.6768	3.5777	−1.0573	0.8007
β_2	0.0033***	0.0004	0.0017***	0.0015***	0.0007
z-Stat.	2.9803	0.4346	5.4449	2.6998	1.0712
β_3	0.0019	0.0024***	0.0015***	0.0010*	0.0017**
z-Stat.	1.2879	2.6625	3.9418	1.8708	2.2083
β_4	0.0011*	0.0028***	0.0014***	0.0007***	0.0016***
z-Stat.	1.7283	5.6271	4.2800	2.9486	4.2823
Variance Eq.					
α_0	0.0001***	8.66E−05***	2.30E−06***	4.19E−07***	6.30E−05***
z-Stat	805.31	16.4651	4.5546	2.6791	19.1812
α_1	−0.0953***	−0.3069***	0.5653***	0.9759***	0.3038***
z-Stat.	−4.2258	−5.2701	6.7191	148.593	6.7304
v_1	−0.2201***	−0.0311	0.1115***	−0.0098***	0.1255***
z-Stat.	−4.6823	−0.8968	3.5111	−2.8175	3.1170
α_2	0.5229***	0.2739	0.0005	0.0184**	0.3861***
z-Stat.	11.0249	8.0701	0.0229	2.1506	10.1443
ζ_1	−3.82E−05***	−9.22E−06	−2.07E−07	−8.01E−08	−5.04E−06
z-Stat.	−3.0963	−1.6372	−1.3947	−0.8505	−1.2868
ζ_2	−6.99E−05***	2.42E−06	−6.34E−07***	4.95E−08	−1.52E−05**
z-Stat.	−3.9500	0.2571	−1.8186	0.2766	−2.5214
ζ_3	−2.89E−05	−1.26E−05	−1.87E−07	2.93E−07	−8.51E−06
z-Stat.	−0.9184	−1.0336	−0.5340	0.8182	−0.8495
ζ_4	−2.93E−05***	−2.39E−05***	−1.47E−07	−3.57E−08	−1.05E−05***
z-Stat.	−3.1037	−6.2215	−1.3493	−0.4986	−3.4407

Notes: Estimates are based on mean Eq. (6) and variance Eq. (7) in the text. ψ_1 is the coefficient of the pairwise conditional correlation (ρ_{t-1}) with 1 lag among USA and BRICS. The lag length is determined by the AIC and SIC criteria (not reported). $\beta_{k,t}$ and $\zeta_{k,t}$, where $k = 1, 2, 3, 4$, are the dummy variable coefficients for the three phases of the GFC and the fourth phase of "stabilization and recovery" (based on financial/economic events, described on subsection 2.2), α_1 is the coefficient of h_{t-1} and α_2 is the asymmetric (GJR) term of the GARCH process a la Glosten et al. (1993).
***, **, and * represent statistical significance at 1%, 5%, and 10% levels, respectively.

Table 6
Tests of changes in dynamic correlations between market stock returns during the phases of GFC (statistical approach).

Mean Eq.	USA–BRA	USA–RUS	USA–IND	USA–CHN	USA–SAF
c_0	0.0088***	0.0025***	0.0002***	0.0007***	0.0027***
z-Stat.	10.0692	6.4442	3.4416	3.7237	6.8159
ψ_1	0.9856***	0.9916***	0.9955***	0.9928***	0.9917***
z-Stat.	600.66	629.60	708.47	606.44	912.46
β_1	0.0033***	0.0001	0.0003*	−0.0004	−0.0007
z-Stat.	4.6253	0.1572	1.7597	−1.2890	−0.7425
β_2	0.0019	0.0030**	0.0011***	0.0014***	0.0012**
z-Stat.	1.3770	2.2542	4.4548	3.5806	2.3059
β_3	0.0017***	0.0022***	0.0008***	0.0007***	0.0015***
z-Stat.	4.2241	5.0036	3.3353	3.3875	4.1464
Variance Eq.					
α_0	0.0001***	8.64E−05***	7.18E−06***	3.73E−07***	6.24E−05***
z-Stat.	24.4708	16.1297	6.9111	13.9449	19.2707
α_1	−0.2109***	−0.3089***	−0.1796	0.9796***	0.3075***
z-Stat.	−8.3178	−5.1155	−1.2583	62.0560	6.8196
v_1	−0.1080***	−0.0428	0.1441***	−0.0100***	0.1199***
z-Stat.	−4.4745	−1.2276	3.6184	−17.0088	2.9565
α_2	0.4585***	0.2789***	0.0560***	0.0170***	0.3811***
z-Stat.	12.9029	8.2560	3.4966	17.0542	9.9460
ζ_1	−5.94E−05***	3.84E−06	−1.61E−06***	−2.68E−07***	1.04E−05
z-Stat.	−5.5533	0.3728	−2.8450	−9.8515	1.2214
ζ_2	−4.46E−05*	−1.51E−05	−1.33E−06**	1.30E−07*	−1.06E−05*
z-Stat.	−1.8199	−0.8346	−1.9906	1.9346	−1.8394
ζ_3	−2.67E−05***	−2.33E−05***	−5.88E−07**	−1.79E−08	−9.45E−06***
z-Stat.	−3.0640	−6.0670	−2.0251	−1.5475	−3.1192

Notes: Estimates are based on mean Eq. (6) and variance Eq. (7) in the text. ψ_1 is the coefficient of the pairwise conditional correlation (ρ_{t-1}) with 1 lag among USA and BRICS. The lag length is determined by the AIC and SIC criteria (not reported). $\beta_{k,t}$ and $\zeta_{k,t}$, where $k = 1, 2, 3, 4$, are the dummy variable coefficients for the two crisis regimes (1a and 1b) and the post-crisis regime (based on regimes of excess volatility, described on subsection 2.2), α_1 is the coefficient of h_{t-1} and α_2 is the GJR term.
***, **, and * represent statistical significance at 1%, 5%, and 10% levels, respectively.

which report signs of contagion before the Lehmann Brothers collapse (phase 1 of initial turmoil) for Russia, the statistical approach does not show a crisis regime during this period. South Africa exhibits contagion during the period from 18th September 2008 until 7th April 2009 (crisis regime 1b), while the results from the economic approach support its immunity for the last months of 2008 (phase 2 of sharp financial market deterioration). This may be due to that the statistical approach treats the second and third phases from the economic approach as an overlapping phase, and thus each phase affects the other, and until the crisis has passed no phase seems to have a clear end point. On the other hand, the dependence among all BRICS and USA is significantly increased during the post crisis regime, which is in line with results based on the economic approach.

Finally, a higher volatility of the correlation structure implies that the stability of the correlation is less reliable for the implementation of investment strategies. However, the dummy variables in variance equation reported in Tables 5 and 6 are either negative or statistically insignificant for all BRICS during the phases of the crisis identified by either the economic or the statistical approach. This finding indicates that correlation coefficient volatility is either decreased or unchanged, helping investors to use it as a guide for portfolio decisions.

4.2.1. Interpretation of the results

The conditional correlation estimates following both crisis identification approaches show a general pattern of decoupling for most of BRICS during the early stages of the crisis, the existence of contagion effects after the Lehman Brothers collapse, although across different periods of the crisis for some markets, and strong evidence of dependence among BRICS and USA from early 2009 onwards (post-crisis period). These findings could be explained as follows. After a decade of growth, BRICSs' economies have built up strong consumer demand accumulated high levels of foreign exchange reserves and significant budget surpluses. These advantages may explain the lagged impact of the crisis for almost all BRICS. Another possible explanation for the decoupling of most BRICS at the beginning of the crisis may be that investors considered the news of the US subprime crisis as a single-country case and the crisis signal has not fully recognized.

However, the severity of the GFC proved insufficient to maintain immunity after mid-September 2008. This may be caused by shifts in investors' common but changing appetite for risk. As the GFC deepens, investors scramble to sell their assets and move into cash producing higher correlations and leading to contagion effects. It seems that, after the Lehmann Brothers collapse, investors' appetite for risk falls and they immediately reduce their exposure to stock markets, which they consider as risky markets. This behavior consequently leads BRICSs' and USA stock markets to fall in value together. This finding is consistent with the DCC paths shown in Fig. 4. Finally, all BRICS exhibit increasing co-movements with USA from early 2009 onwards, indicating that dependence is smaller in bearish than in bullish markets. This might imply a low probability of simultaneous crashes and is in line with Aloui et al. (2011).

The contagion results in BRICS during different periods of the GFC seem to be unrelated to their trade and financial characteristics. Table 7 presents the trade and financial profiles of BRICS during the period 2007–2009. The trade characteristics of Brazil and Russia reveal more sensitive revenues from exports of commodity products (commodity-price dependent markets), while the economic performance of China, India and South Africa depends greatly on exports of manufactured products (finished-product export-oriented markets). Additionally, it is worth noting that both China and South Africa have a high degree of economic openness, measured by trade to GDP ratios, while India and Brazil have the lowest degree. Our evidence based on both crisis identification approaches does not show a pattern of contagion for all markets that could be attributed to their common trade characteristics. Indeed, almost all markets are decoupled at the beginning of the GFC, while contagion appears faster in India than in China and South Africa, and the crisis seems to affect the two commodity-price dependent markets (Brazil and Russia) during different crisis periods. These results contrast, to some extent, the findings of Aloui et al. (2011), who support stronger dependency for Brazil and Russia, than India and China with USA.

Table 7
Trade and financial profiles of BRICS.

	2007	2008	2009
Brazil			
Exports of commodities — % of merchandise exports	49.46	52.69	58.68
Exports of manufactures — % of merchandise exports	47.84	44.84	39.46
Trade to GDP ratio (%)	25.20	27.13	22.11
Market capitalization (% of GDP)	100.32	35.65	71.98
Turnover ratio (%)	56.20	74.27	73.90
Russia			
Exports of commodities — % of merchandise exports	74.96	75.07	77.95
Exports of manufactures — % of merchandise exports	16.95	16.73	17.20
Trade to GDP ratio (%)	51.70	53.38	48.43
Market capitalization (% of GDP)	115.64	23.91	70.45
Turnover ratio (%)	58.94	59.17	108.45
India			
Exports of commodities — % of merchandise exports	34.63	35.61	28.76
Exports of manufactures — % of merchandise exports	64.20	62.78	66.81
Trade to GDP ratio (%)	44.87	52.26	45.63
Market capitalization (% of GDP)	146.85	52.73	86.64
Turnover ratio (%)	83.96	85.18	119.34
China			
Exports of commodities — % of merchandise exports	6.74	6.88	6.28
Exports of manufactures — % of merchandise exports	93.07	92.98	93.57
Trade to GDP ratio (%)	68.02	62.24	49.01
Market capitalization (% of GDP)	178.19	61.78	100.32
Turnover ratio (%)	180.10	121.29	229.60
South Africa			
Exports of commodities — % of merchandise exports	48.2870	47.70	52.47
Exports of manufactures — % of merchandise exports	51.5969	52.22	47.48
Trade to GDP ratio (%)	65.5180	74.61	55.66
Market capitalization (% of GDP)	291.27	179.38	249.04
Turnover ratio (%)	54.98	60.61	57.26

Notes: This table presents the trade profiles and some financial characteristics of BRICS markets during the period 2007–2009. The total exports of commodity products are equal to the sum of the exports of agricultural raw materials, food, fuel, ores and metal products. Trade to GDP ratio is the sum of exports and imports of goods and services measured as a share of gross domestic product. Market capitalization of listed companies is in percentage of GDP. Turnover ratio corresponds to the value of shares traded during a year divided by the average market capitalization for a year. Data are obtained from World Development Indicators database.

Finally, the financial profiles of the BRICSs' markets are also different. South Africa and China have the highest ratios of market capitalization to GDP and Russia and Brazil the lowest ones, while the most liquid markets (measured by turnover to market capitalization) are China and India and the less liquid are Brazil and South Africa. A similar pattern of contagion for deeper and more liquid markets would be expected, since these financial characteristics may serve as channels of contagion. However, these financial variables seem to be irrelevant to the correlation dynamics of BRICS during the GFC.[11]

5. Conclusions

The spread of the GFC from US to BRICSs' stock markets is being analyzed using a multivariate AR(1)–FIAPARCH (1,d,1)–DCC specification. A preliminary analysis shows that this model is appropriate to capture long memory behavior, speed of market information, asymmetries and leverage effects of the examined equity markets.

The length and the phases of the crisis are identified based on all key international financial/economic events that represent the GFC and regimes of excess volatility for each emerging market. The statistical analysis of correlation coefficients during the several phases of the crisis supports a general pattern of decoupling for some of BRICSs' markets (Brazil, China and S. Africa) at the early stages of the GFC, and a recoupling for almost all markets after the failure of Lehman Brothers. These findings do not show a pattern of contagion for all markets that could be attributed to their common trade and financial characteristics. They also indicate the increasing co-movement among USA and BRICS during the post-crisis period (from early 2009 onwards), implying that dependence is larger in bullish than in bearish markets. This might indicate a low probability of simultaneous breakdown of markets.

These results imply that investors should be cautious about simultaneously investing in markets that exhibit pure contagion, since a shift in investors' risk appetite is likely to disappear the portfolio benefits when are most wanted. From policy makers' perspective, this study provides important information about the directions for possible undertaking measures in order to protect emerging markets from contagion during future crises. They should carefully examine and uncover possible decoupling strategies that may insulate emerging markets from contagion. Specifically, when a decline in investors' appetite for risk occurred after a period of high risk appetite, markets will have a high tendency to react adversely to events that might not otherwise warrant major reaction. In these circumstances, it may be appropriate to provide funding expeditiously to stabilize sentiment and have lighter conditionality (Kumar & Persaud, 2001). Increasing liquidity quickly could substantially reduce the magnitude of a crisis and potential contagion effects.

Finally, future research could empirically investigate the impact of different types of economic structure on the interrelationships among BRICS and developed financial markets, as well as the transmission of the crisis in their real economies by using country-specific fundamentals.

[11] The connection of BRICSs' economic and financial structure to the contagion dynamics needs further analysis in terms of quantifying the impact of macroeconomic and financial variables on stock markets' behavior.

References

Aloui, R., Aissa, M. S. B., & Nguyen, D. K. (2011). Global financial crisis, extreme interdependences, and contagion effects: The role of economic structure? *Journal of Banking and Finance*, *35*, 130–141.
Baur, D. G. (2012). Financial contagion and the real economy. *Journal of Banking and Finance*, *36*(10), 2680–2698.
Bekaert, G., & Harvey, C. R. (1995). Time-varying world market integration. *Journal of Finance*, *50*(2), 403–444.
BIS (2009). *The international financial crisis: Timeline, impact and policy responses in Asia and the Pacific.* Bank for International Settlements.
Boyer, B. H., Kumagai, T., & Yuan, K. (2006). How do crises spread? Evidence from accessible and inaccessible stock indices. *Journal of Finance*, *61*(2), 957–1003.
Celic, S. (2012). The more contagion effect on emerging markets: The evidence of DCC–GARCH model. *Economic Modelling*, *29*, 1946–1959.
Chan, K. F., Treepongkaruna, S., Brooks, R., & Gray, S. (2011). Asset market linkages: Evidence from financial, commodity and real estate assets. *Journal of Banking and Finance*, *35*, 1415–1426.
Chiang, T. C., Jeon, B. N., & Li, H. (2007). Dynamic correlation analysis of financial contagion: Evidence from Asian markets. *Journal of International Money and Finance*, *26*, 1206–1228.
Chkili, W., Aloui, C., & Ngugen, D. K. (2012). Assymetric effects and long memory in dynamic volatility relationships between stock returns and exchange rates. *Journal of International Markets, Institutions and Money*, *22*, 738–757.
Conrad, C., Karanasos, M., & Zeng, N. (2008). *Multivariate fractionally integrated APARCH modeling of stock market volatility: A multi-country study. Discussion paper series, No. 472*, University of Heidelberg.
Conrad, C., Karanasos, M., & Zeng, N. (2011). Multivariate fractionally integrated APARCH modeling of stock market volatility: A multi-country study. *Journal of Empirical Finance*, *18*, 147–159.
Dooley, M., & Hutchison, M. (2009). Transmission of the U.S. subprime crisis to emerging markets: Evidence on the decoupling–recoupling hypothesis. *Journal of International Money and Finance*, *28*, 1331–1349.
Dungey, M., Fry, R., González-Hermosillo, B., & Martin, V. (2005). Empirical modeling of contagion: A review of methodologies. *Quantitative Finance*, *5*, 9–24.
Engle, R. F. (2002). Dynamic conditional correlation — A simple class of multivariate GARCH models. *Journal of Business and Economic Statistics*, *20*, 339–350.
Federal Reserve Board of St. Louis (2009). *The financial crisis: A timeline of events and policy actions.*
Forbes, K., & Rigobon, R. (2002). No contagion, only interdependence: Measuring stock market comovements. *Journal of Finance*, *57*, 2223–2261.
Geweke, J., & Porter-Hudak, S. (1983). The estimation and application of long-memory time series models. *Journal of Time Series Analysis*, *4*, 221–238.
Glosten, R. T., Jagannathan, R., & Runkle, D. (1993). On the relation between the expected value and the volatility of the nominal excess return on stocks. *Journal of Finance*, *48*, 1779–1801.
Hosking, J. R. M. (1980). The multivariate portmanteau statistic. *Journal of the American Statistical Association*, *75*, 602–608.

Kaminsky, G., Reinhardt, C., & Vegh, C. (2003). The unholy trinity of financial contagion. *Journal of Economic Perspectives*, *17*, 51–74.
Kenourgios, D., & Padhi, P. (2012). Emerging markets and financial crises: Regional, global or isolated shocks? *Journal of Multinational Financial Management*, *22*, 24–38.
Kenourgios, D., Samitas, A., & Paltalidis, N. (2011). Financial crises and stock market contagion in a multivariate time-varying asymmetric framework. *International Financial Markets, Institutions and Money*, *21*, 92–106.
Kumar, S. M., & Persaud, A. (2001). Pure contagion and investors' shifting appetite: Analytical issues and empirical evidence. *IMF Working Paper, WP/01/134*.
Lo, A. W. (1991). Long term memory in stock market prices. *Econometrica*, *59*, 1279–1313.
McLeod, A. I., & Li, W. K. (1983). Diagnostic checking ARMA time series models using squared residual autocorrelations. *Journal of Time Series Analysis*, *4*, 269–273.
Pericoli, M., & Sbracia, M. (2003). A primer on financial contagion. *Journal of Economic Surveys*, *17*(4), 571–608.
Robinson, P. M. (1995). Log-periodogram regression of time series with long range dependence. *The Annals of Statistics*, *23*, 1048–1072.
Samarakoon, L. P. (2011). Stock market interdependence, contagion and the U.S. financial crisis: The case of emerging and frontier markets. *Journal of International Financial Markets, Institutions & Money*, *21*, 724–742.
Syllignakis, M., & Kouretas, G. (2011). Dynamic correlation analysis of financial contagion: Evidence from the Central and Eastern European markets. *International Review of Economics and Finance*, *20*, 717–732.
Tse, Y. K. (1998). The conditional heteroscedasticity of the yen–dollar exchange rate. *Journal of Applied Econometrics*, *13*, 49–55.
Tse, Y. K., & Tsui, A. K. C. (2002). A multivariate generalized autoregressive conditional heteroscedasticity model with time-varying correlations. *Journal of Business & Economic Statistics*, *20*(3), 351–362.