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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.



## 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

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[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 $\delta$ ($\delta > 0$) is a Box–Cox transformation of $h_t$, $\gamma$ is the leverage coefficient, while $(1\text{–}L)^{d}$ 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, $\theta_1$ and $\theta_2$ 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 $\alpha$ and $\beta$ 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: $R_t = (diag(Q_t))^{-1/2} Q_t (diag(Q_t))^{-1/2}$.