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Global financial crisis and spillover effects among the U.S. and BRICS stock markets

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Abstract. This article examines the spillover effect between the U.S. market and five of the most important emerging stock markets namely the BRICS (Brazil, Russia, India, China and South Africa), and draws implications for portfolio risk modeling and forecasting. It gives consideration to periods before and after the recent global financial crisis (GFC). To this end, the bivariate DCC-FIAPARCH model, the modified ICSS algorithm and the Value-at-Risk (VaR) are employed to capture volatility spillovers, detect potential structural breaks and assess the portfolio market risks. Using the U.S. and the BRICS daily spot market indices for the period from September 1997 to October 2013, our empirical results show strong evidence of asymmetry and long memory in the conditional volatility and significant dynamic correlations between the U.S. and the BRICS stock markets. Moreover, we find several sudden changes in these markets with a common break date centered on September 15, 2008 which corresponds to the Lehman Brothers collapse. The Brazil, India, China and South Africa markets are strongly affected by the GFC, supporting the hypothesis of recoupling (with increased linkages). In contrast, the hypothesis of decoupling is supported for the Russian stock markets only. Finally, the skewed Student-t FIAPARCH models outperform and provide more accurate in-sample estimates and out-of-sample forecasts of VaR than the normal and Student-t FIAPARCH models in almost all cases. These results provide helpful information to financial risk managers, regulators and portfolio investors to determine the diversification benefits among these markets.

JEL classification: G14; G15.
Keywords: Volatility spillovers; global financial crisis; structural breaks; VaR forecasts; multivariate DCC-FIAPARCH.

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1. Introduction

BRICS, as identified by Goldman Sachs, is the acronym bestowed on a group of the five fast growing markets in the universe of emerging market economies. This group includes Brazil, Russia, India, China and South Africa. These economies are distinguished from other emerging market economies by their demographic potential and promising economic perspective. Therefore, the BRICS have attracted a great deal of attention from investors, regulators, financial agencies, portfolio managers, policymakers and financial media. Together, these economies account for more than 40% of the world's population and rank among the world's largest and most influential countries in the 21st century. In particular, China and India are among the countries that experience the highest global economic growth over the last 15 years. It is also expected that the four BRIC countries (excluding South Africa) account for 41% of the world's stock market capitalization and China alone become the largest equity market in the world by 2030 (Hammoudeh et al., 2013; Liu et al., 2013).

Similar to other emerging markets, the BRICS markets share several interesting features in common. They have consistently produced high average returns with relatively low correlations with those of developed markets. However, their returns are relatively more predictable and volatile than those of the developed markets. Barry et al. (1998) document that some of today's emerging markets have become some of tomorrow's developed markets, which is likely to apply to the BRICS markets. These features also show that emerging markets have become an important asset class and that their holdings in international and dedicated portfolios are of growing significance since they present diversification benefits for investors in the developed markets.

These favorable characteristics of the BRICS markets can largely be explained by the gradual financial liberalization process that has started in the majority of emerging markets in early 1980s and by the wave of financial and economic reforms that followed. This

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transformation process has principally extended the emerging markets' investors base by allowing foreign investors to hold domestic market assets. It has also made emerging markets more liquid, increased their credibility, visibility and transparency, improved their market size and depth, and strengthened investor protection particularly the minority shareholders. In a more recent study, Buchanan et al. (2011) highlight the importance of including the emerging market asset class in developed markets' portfolios as it enables investors to achieve higher risk-adjusted performance.

On the other hand, the onset of the GFC which is deemed as the worst crisis since the Great Depression of the 1930s, has called for a careful investigation of the trade-off between return-seeking behavior in international markets and high risks from contagion owing to the increased financial openness and market integration. While the higher integration of financial markets around the world has enabled free capital mobility, it has also led to increasing volatility spillovers, particularly between emerging and developed markets. Indeed, emerging markets are very sensitive and vulnerable to external shocks coming from developed markets particularly the United States, due to the weakness and immaturity of their financial institutions and regulatory systems. The successive financial and currency crises over the last two decades are the ideal situations to observe the sharp changes in market interdependence and volatility transmission. For instance, King and Wadhwani (1990) find that Japan, the U.S. and the U.K. stock market correlations have significantly increased following the stock market crash in 1987. Similar results are obtained by Dimitriou et al. (2013) for the BRICS stock markets, and Toyoshima and Hamori (2013) for the Japan and Singapore stock markets.

Given their specificities and the important role they play in the global economy in terms of both market share and economic growth, the BRICS emerging markets need special research in several ways, predominantly in terms of volatility spillovers with the United States. This research aims to examine the dynamic spillovers between the five fast growing

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BRICS economies and the world's most important developed market of the United States, with emphasis on the GFC of 2008-2009. The U.S. market is selected based on its size and influence on the international stock markets and it is also the U.S. economy from where the GFC originated and spread to other economies. We investigate, in particular, the spillover effects of the GFC on the volatility transmission between the United States and the BRICS. We then provide the financial implications of the volatility spillovers in regard to portfolio risk management through an analysis of in- and out-of-sample Value at Risk (VaR) forecasts for portfolios of the emerging and U.S. stocks under consideration.

Empirically, we adopt the multivariate Dynamic Conditional Correlation Fractionally Integrated Asymmetric Power ARCH (DCC-FIAPARCH) model to investigate the spillover effects between the daily spot indices of the U.S. stock markets and BRICS over the period spanning the period September 29, 1997 to October 14, 2013. This model accommodates several most important stylized facts of stock returns such as the persistence, long memory and asymmetry properties of the conditional variance processes (see, e.g., Cont, 2001). Our emphasis is on the changes in those properties as a result of the onset of the GFC which has implications for market contagion, portfolio allocation and risk management.

This empirical approach which nests the FIAPARCH model of Tse (1998) and the DCC specification of Engle (2002) thus allows one to synergize their advantages. Specifically, the FIAPARCH models offer the flexibility to model the conditional second moment taking into account the long memory property, the predictability structure of return volatility and the volatility asymmetric characteristics (i.e., negative shocks to stock prices have greater effects on the conditional volatility than positive shocks of the same magnitude). For its part, the DCC modeling provides an efficient way to capture the conditional correlations among the sample markets which change through time with respect to market conditions. This extended model is also less restrictive in terms of the number of variables

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included, compared to other multivariate volatility models such as the full BEKK-GARCH model and the VEC-GARCH model. Ahmad et al. (2013) suggest that the estimated parameters of DCCs allow one to analyze in depth the changes in correlation during the stability/crisis periods.

Our study makes a number of contributions to the existing literature. First, it examines the dynamic linkages of the BRICS stock markets with the United States which is the largest developed stock market. The BOVESPA index, the RTS index, the BSE SENSEX index, the Shanghai Composite index, and the FTSE/JSE index are used as the representative portfolios for the Brazilian, Russian, Indian, Chinese, and South African stock markets, respectively. The S&P500 index is also used as the representative for the stock market of the United States since it provides an accurate proxy for a diversified equity portfolio and has long been seen as the benchmark for measuring portfolio performance. Second, to the extent that financial crises and their associated spillover effects may directly affect return and volatility structures, we investigate how the GFC of 2008-2009 impacts the spillovers among the BRICS and the dominant U.S. markets. It is worth noting that we take the GFC effects into account by first detecting the potential of structural breaks with the use of the adjusted iterative cumulative sum of squares (ICSS) algorithm of Sanso et al. (2004) which modified the original Inclán and Tiao (1994) procedure in order to differentiate between the impacts of the tranquil or stable period and the volatile/crisis period. Third, we estimate our DCC-FIAPARCH model which explicitly accommodates long-range memory shifts, leverage effects and asymmetry in the volatility processes during both periods. Finally, we analyze the implications of the estimation results on portfolio decision making and risk forecasting. More specifically, we show how these results help improve the portfolio’s VaR forecasting for both short and long positions.

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On the whole, using the pairwise Granger causality tests as a preliminary analysis, we find that the U.S. stock market Granger-causes each of the BRICS stock markets (the results are not provided in this study but are available upon request). In addition, there is evidence of significant cross volatility effects between the U.S. and those five emerging indices. We detect seven structural breaks for the U.S. stock markets and at least ten such breaks for the BRICS stock markets, which may account for the importance of regional and local events, in addition to global factors. The date of September 15, 2008 is generally found as a common break date for the sample markets. This break date corresponds to the occurrence of the bankruptcy of Lehman Brothers, which sparked off the severe period of the GFC. We also show a linkage between the U.S. and each of BRICS stock markets except Russia, supporting the phenomenon of heightened recoupling for most of the BRICS after the Lehman Brothers collapse. For the Russian case, we do not find spillovers from the U.S. market to the Russian market after the Lehman Brothers collapse, indicating a sign of decoupling between these two markets. Finally, the skewed Student-t FIAPARCH model is the most suitable specification for improving the VaR forecasting efficiency.

The remainder of this study is organized as follows. Section 2 presents a brief review of the literature. Section 3 discusses the methodology used in this study. Section 4 describes the data and conducts some preliminary analysis. Section 5 reports the empirical results. Section 6 provides concluding remarks.

2. Literature review

One of the key challenges for market participants (e.g., individual investors, institutional investors, traders, portfolio managers, policy makers, etc.) is to understand the volatility of stock markets and the volatility transmission between them, especially between emerging and developed stock markets after a major crisis strikes. Indeed, these market

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participants are mindful of portfolio losses and systematic risk particularly during crises and contagious shocks and when they invest simultaneously in stock markets of different countries. The recent financial crisis has severely affected the market microstructure as such investment, liquidity, asset pricing and financial risk management of the frontier, emerging and developed economies. As international capital markets have become more and more integrated with each other, a number of studies have addressed the issue of market comovement and interdependence, particularly with careful consideration of financial crisis periods.

Using daily open-to-close, close-to-open, and intraday data over the period from August 1, 1991 to December 31, 1992, Wei et al. (1995) test the volatility transmission between developed and emerging stock markets, and also question the effects of market openness on return and volatility spillovers. They provide evidence of significant spillover effects from developed to emerging markets. On the other hand, Wang et al. (2003) study the dynamic causal linkages between the five largest emerging African stock markets and the U.S. market over the 1997/1998 Asian financial crisis. These authors show evidence that both the short-run causal linkages and the long-run relationships between these markets are substantially weakened after that crisis. Aloui et al. (2011) use a GARCH-copula approach to analyze the conditional dependence structure between the four BRIC and the U.S. stock markets and find strong evidence of time-varying dependence between each of those BRIC markets and the U.S. market. However, the dependency is stronger for the more commodity price-dependent BRIC markets (Brazil and Russia) than for the finished-product export-oriented markets (India and China). They also observe high levels of dependence persistence for all market pairs during both bullish and bearish markets

In another study that deals with emerging markets, Bhar and Nikolova (2009) use the bivariate EGARCH model to examine the level of integration and the dynamic relationship

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between the four BRIC countries (Brazil, Russia, India and China), other regions and the world. They find that India shows the highest level of regional and global integration among those BRIC countries, followed by Brazil, Russia, and China. In addition, their results provide strong evidence of a negative volatility relationship between the Indian and the Asia-Pacific regional markets, and between the Chinese and the world markets, which suggests potential diversification opportunities for portfolio investors. Using the same model as in Bhar and Nikolova (2009), Abbas et al. (2013) investigate the presence of volatility transmission among regional Asian equity markets (Pakistan, China, India and Sri Lanka) and three regional and developed stock markets (United States, United Kingdom and Singapore). These authors find evidence of significant volatility spillovers between friendly countries of different regions that have economic links. Moreover, there is evidence of volatility transmission between countries which are on unfriendly terms among regional equity markets including Pakistan, China, India and Sri Lanka.

By applying the trivariate VAR-GARCH models for 41 emerging markets in Asia, Europe, Latin America, and the Middle East and North Africa (MENA), Beirne et al. (2010) find volatility spillovers from regional and global markets to the majority of emerging markets.[1] Moreover, the nature of the cross-market linkages varies across countries and regions. However, the return spillovers dominate the transmissions in emerging Asia and Latin America, while the spillovers in variance appear to play a key role in emerging Europe. Finally, the relative importance of the regional and global spillovers varies, with the global spillovers dominating in Asia while the regional spillovers prevail in Latin America and the Middle East. Bekiros (2014) examines the responsiveness of the BRIC markets to the international return and volatility shocks after the recent U.S. financial crisis and the

[1] The global market returns are calculated as a weighted average of the returns of the stock market indices of the United States, Japan, and Europe (France, Germany, Italy, and United Kingdom). The regional market returns are calculated as a weighted average of the returns of the stock market indices of all sample emerging markets in the region, except the local market.

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subsequent Eurozone sovereign debt crisis. The author shows that almost all markets have become more internationally integrated after those crises.

In a recent study, Chiang et al. (2013) investigate the spillover effects of returns and volatility of the U.S. stock market on the stock markets of Brazil, Russia, India, China and Vietnam (BRICV) by using the autoregressive conditional jump intensity (ARJI) model. They reveal that Russia receives the greatest contagious effects of returns and volatility from the U.S. market before the 2007/2008 financial crisis, while Vietnam is the receiver of the most intense spillover effects following this crisis. In addition, India exhibits the lowest long-run total risk, while the greatest risk is found for China and Brazil.

Several studies employ the DCC-GARCH model to show the contagion of the GFC for emerging stock markets, especially for the BRICS markets. Xu and Hamori (2012) examine the dynamic linkages between the BRIC countries and the United States (as represented by Dow Jones Industrial Average Index) in the mean and variance of the stock prices for the pre- and post-2007/2008 crisis periods.[2] They show that the international transmission of stock prices between the BRICs and the United States weaken in both the mean and variance during the GFC. Hwang et al. (2013) study the time-varying conditional correlations among the United States and emerging stock markets including the BRICS, South Korea, Thailand, Philippines, Taiwan, and Malaysia, and find different patterns of spillovers among these emerging economies due to the U.S. financial crisis . They also show that increases in the credit default swaps (CDS) spread and the TED spread (i.e., the yield difference between the three-month LIBOR and the US three-month Treasury bills) decrease the conditional correlations. However, increases in the foreign institutional investment,

[2] Given the drastic plunge of the U.S. stock market index on September 28, 2008 that reached 6.9%, those authors select this date as a break point in order to divide the entire sample period into the pre-crisis period and the during and post-crisis period.

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exchange market volatility, and the implied volatility (VIX) on the S&P 500 index are found to drive up the conditional correlations.

Using an event study regression, Dooley and Hutchison (2009) find that over the period from January 1, 2007 to February 19, 2009, a range of financial and real economic news emanating from the U.S. has statistically and economically large significant impacts on the 5-year CDS spreads on sovereign bonds of fourteen emerging markets and that several news events uniformly move markets. The authors address the "decoupling–recoupling" topic by examining the changes in the structural linkages between the U.S. and emerging markets. Their results support the hypothesis of decoupling (signs of isolation) between emerging markets from early 2007 to summer 2008. However, those authors find re-coupling (linkage) among those markets early fall 2008, confirming the results of the existing literature that the recent GFC has severe repercussions on emerging markets.

Similarly, Ahmad et al. (2013) apply the multivariate DCC-GARCH model to examine the financial contagion effects of the GIPSI countries, the United States, UK, Japan markets on the BRIICKS stock markets over the period 1996-2012.[3] During the Eurozone debt crisis period, the authors show that Ireland, Italy and Spain appear to be the most contagious to the BRIICKS markets, compared with the contagion coming from Greece. Moreover, their results also indicate that Brazil, Russia, India, China and South Africa are strongly hit by the contagion shocks from the GIPSI stock markets. More importantly, Bianconi et al. (2013) explore the behavior of the stocks and bonds in the BRIC countries, and find that the DCC estimates between the stock returns, bond returns and a U.S. financial stress indicator have increased after the Lehman Brothers collapse.[4]

[3] The acronym GIPSI refers to Greece, Ireland, Portugal, Spain and Italy, while BRIICKS represents Brazil, Russia, India, Indonesia, China, South Korea and South Africa.
[4] To understand how volatility spreads between the BRICS countries, those authors use the heat map measure. For further information, see the IMF reports (2008; 2009).

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More recently, Zhang et al. (2013) use the DCC decomposing method and show that the 2007/2008 financial crisis causes a permanent change in the long-term correlations between the BRICS and developed (U.S. and Europe) stock markets. They find strong evidence that the recent GFC has changed the conditional correlation relationships between the emerging BRICS and developed stock markets. More precisely, the stock markets in Brazil and Russia have stronger correlations with developed countries than with India and China. Taking in consideration the asymmetric effects, the study of Gjika and Horváth (2013) adopts the Asymmetric DCC (ADCC)-GARCH model to examine the time-varying co-movements of the stock markets in the Central Europe, and finds evidence of strong correlations among those markets and between them and markets in the euro area countries.

Applying the multivariate constant conditional correlations FIAPARCH model (CCC-FIAPARCH) for eight national stock indices namely FTSE 100 (UK), S&P 500 (US), DAX 30 (Germany), CAC 40 (France), Nikkei 225 (Japan), Straits Times (Singapore), Hang Seng (Hong Kong) and TSE 300 (Canada) within the period 1988-2003, Conrad et al. (2011) suggest that the conditional volatility of these eight indices that are considered is best modeled as a FIAPARCH process. Additionally, both the optimal fractional differencing LM parameter and the power transformation coefficient are remarkably similar across the eight countries.

Dimitriou et al. (2013) extend the methodology of Conrad et al. (2011) to investigate the contagion effects of the GFC on the BRICS and the U.S. stock markets. They employ the multivariate DCC-FIAPARCH model but fail to find evidence of support for a contagion effect for most of the BRICS markets during the early stages of the crisis. The linkage however re-emerged after the Lehman Brothers bankruptcy, indicating a shift in investors' risk appetite. The authors show large dependence between the BRICS and the United States from early 2009 onwards. The dependence is larger in the bullish than the bearish markets.

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In all, our research is totally different from the aforementioned studies. Indeed, all the cited works do not test the dynamic correlation before and after the Lehman Brothers collapse. Additionally, they do not consider the VaR forecasting analysis, which we take into account in this study and apply it to the BRICS markets. These are the major contributions of our work.

Our study complements the related literature since we deal with the issue of volatility spillover effects between the BRICS and the U.S. stock markets, while accommodating the long memory, volatility power, volatility asymmetry, and structural breaks properties. The repercussions of the onset of the GFC on the time-varying conditional correlations among the U.S. and BRICS stock markets are also considered in this analysis. We also go beyond this analysis by showing the impacts of the empirical results on the forecasting of portfolio market risks for both short- and long positions.

Empirically, the aforementioned individual models of the GARCH-based model family have some drawbacks as they do not consider all stylized facts (as shown in the descriptive statistics). For example, the bivariate EGARCH model, the DCC-GARCH model, the ADCC-GARCH model and the AR conditional jump intensity model do not account for the long memory process in asset series. Concerning the CCC-FIAPRCH model, it assumes in this model that the conditional correlation is stable over time, which is not realistic. In fact, the correlations are of great relevance for many of the common tasks of financial management. Forecasting, asset allocations and portfolio risk assessments require estimates of correlations between return series. If correlations and volatilities are changing, then portfolios should be rebalanced according to the most recent information. Thus, building an optimal portfolio requires having a model with dynamic correlations. In the literature, there is unanimity on the dynamic behavior of the conditional correlations since the pioneering work of Engle (2002). The DCC model is thus proposed because the conditional correlations are not constant but are

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time-varying. As for the bivariate DCC-FIAPARCH model applied in our study, this model embraces the majority of stylized facts, thus is more comprehensive and realistic than the standard GRACH models. It increases the flexibility of the conditional variance specifications by allowing: (i) an asymmetric response of volatility to positive and negative shocks (i.e., being able to trace the leverage effect); (ii) the data to determine the power of returns for which the predictable structure in the volatility pattern is the strongest; (iii) the long memory to be accounted for in volatility dependence, depending on the differencing parameter *d*; and (iv) the conditional correlation to be time-varying. These features in the volatility processes of asset returns have major implications for asset allocations, optimal portfolio design, benefits of portfolio diversification, and Value at Risk (VaR) forecasting analysis. It is also worth noting that the FIAPARCH model is very flexible since it nests two major classes of ARCH-type models: the APARCH and the FIGARCH models. For a robust analysis and a fresh new look at spillover effects, the time-varying conditional correlations are assessed within a bivariate FIAPARCH model. This process is well suited to investigate financial contagion since it focuses on the dynamics of the second order moment of financial time-series and overcomes the heteroskedasticity problem when measuring correlations, as raised by Forbes and Rigobon (2002).

3. Econometric modeling framework

This section describes the empirical methods implemented in this study. It begins with the multivariate DCC-FIAPARCH model, followed by the adjusted version of the Inclán and Tiao (1994)'s test for structural breaks and ends with the VaR forecasting analysis.

3.1 The multivariate DCC-FIAPARCH model

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We assume that the return-generating process can be described by an AR(1) model in which the dynamics of current stock returns are explained by their lagged returns. The AR (1) model is defined as follows

$$(1-\xi L)r_t = \mu + \varepsilon_t \,,\ t \in \mathrm{N} \,, \text{with } \varepsilon_t = z_t\sqrt{h_t} \,, \tag{1}$$

where, $|\mu| \in [0,\infty)$, $|\xi| < 1$ and the innovations $\{z_t\}$ are an independently and identically distributed (i.i.d) process $(z_t \sim N(0,1))$. The conditional variance h_t is positive with probability one and is a measurable function of the variance-covariance matrix, Σ_{t-1}.

The FIGARCH (p,d,q) model is expressed as follows

$$h_t = \omega(1-\beta(L))^{-1} + \left[1-(1-\beta(L))^{-1}\phi(L)(1-L)^d \varepsilon_t^2\right], \tag{2}$$

where ω, β, ϕ, and d are the parameters to be estimated, and $0 \le d \le 1$. L denotes the lag operator. The FIGARCH model provides a greater flexibility for modeling the conditional variance and can distinguish between the covariance stationary GARCH model for $d = 0$ and the non-stationary IGARCH model when $d = 1$, while for $0 < d < 1$ the FIGARCH model is sufficiently flexible to allow an intermediate range of persistence.

Tse (1998) extends the FIGARCH model into FIAPARCH model by adding the function $(|\varepsilon_t| - \lambda\varepsilon_t)^\delta$ of the APARCH. This model is given by

$$h_t^{\delta/2} = \omega(1-\beta(L))^{-1} + \left[1-(1-\beta(L))^{-1}\phi(L)(1-L)^d\right](|\varepsilon_t| - \lambda\varepsilon_t)^\delta, \tag{3}$$

where δ is the power term of returns for the predictable structure in the volatility persistence and $\lambda > 0$ means that negative shocks give rise to higher volatility than positive shocks do. The FIAPARCH model is superior to the FIGARCH model in the sense that it can detect the presence of both asymmetry and long memory in the conditional volatility (Tse, 1998).

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As we attempt to evaluate the volatility spillovers across several BRICS and United States markets, a multivariate FIAPARCH model needs to be set up. We decide to model the structure of conditional correlations by using the DCC approach of Engle (2002). The latter allows us to not only investigate the time-varying correlations across the sample markets, but also to insure the positive definiteness of the variance-covariance matrix (H_t) under simple conditions imposed on specific parameters. The parameterization of a DCC-FIAPARCH model allows for directly inferring the time-varying correlations between the United States and BRICS stock markets and for dealing with a relatively large number of variables in the system, without having a numerical convergence problem at the estimation stage. In the general multivariate case which we use, the variance-covariance matrix of the residuals is defined as follows

$$H_t = D_t R_t D_t \tag{4}$$

where $D_t = diag\left(h_{11t}^{1/d} \cdots\cdots h_{NNt}^{1/2}\right)$ is the $(N \times N)$ diagonal matrix of conditional standard deviations of the residuals, which are obtained from taking the square root of the conditional variance modelled by an univariate AR(1)-FIAPARCH $(1, d, 1)$ model. Moreover, R_t is a matrix of time-varying conditional correlations, which is given by

$$R_t = \left[\rho_{ij,t}\right] = \left(diag(Q_t)\right)^{-1/2} Q_t \left(diag(Q_t)\right)^{-1/2}, \tag{5}$$

The $(N \times N)$ symmetric positive-definite matrix Q_t depends on the squared standardized residuals $\left(u_{i,t} = \varepsilon_{i,t} / \sqrt{h_{ii,t}}\right)$, the unconditional variance-covariance matrix $(\bar{Q})$, and its own lagged value according to Eq. (6) as

$$Q_t = \left(1 - \kappa_1 - \kappa_2\right)\bar{Q} + \kappa_1 u_{t-1} u_{t-1}^{'} + \kappa_2 Q_{t-1}, \text{ with } \kappa_1, \kappa_2 > 0 \text{ and } \kappa_1 + \kappa_2 < 1 \tag{6}$$

The $(N \times N)$ variance-covariance matrix of $\left(u_{i,t} = \varepsilon_{i,t} / \sqrt{h_{ii,t}}\right)$ is given by

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$$\psi_{t-1} = \frac{\sum_{m=1}^{M} u_{i,t-m} u_{j,t-m}}{\sqrt{\left(\sum_{m=1}^{M} u_{i,t-m}^2\right)\left(\sum_{m=1}^{M} u_{j,t-m}^2\right)}} \;,\; 1 \le i \le j \le M \;, \tag{7}$$

where $u_{i,t}$ are the standardized residuals calculated from the residuals of the univariate AR(1)-FIAPARCH $(1, d, 1)$ model.

We can then derive the correlation coefficient in a bivariate case between those emerging and United States markets at time *t* from Eqs. (6)-(7) as follows

$$\rho_{ij,t} = (1 - k_1 - k_2)\rho_{ij} + k_2 \rho_{ij,t} + k_1 \frac{\sum_{m=1}^{M} u_{j,t-m} u_{j,t-m}}{\sqrt{\left(\sum_{m=1}^{M} u_{i,t-m}^2\right)\left(\sum_{m=1}^{M} u_{j,t-m}^2\right)}}, \tag{8}$$

The parameters of the DCC-FIAPARCH model are estimated by using the quasi-maximum likelihood (QML) method with respect to the log-likelihood function in Eq. (9) and according to a two-step estimation procedure.

$$I_t(\theta, \Phi) = -\frac{1}{2}\left[\sum_{t=1}^{T} (n \log(2\pi)) + \log|D_t|^2 + \varepsilon_t D_t^{-2} \varepsilon_t + \sum_{t=1}^{T} \left(\log|C_t| + u_t C_t^{-1} u_t - u_t u_t\right)\right],$$

(9)

In the first stage, we fit the univariate FIAPARCH$(1, d, 1)$model for each of the return series and obtain the estimates of $h_{ii,t}$. In the second stage, the estimated parameters of the first stage are used to compute the dynamic conditional correlations.

3.2. The adjusted ICSS algorithm

Several structural break tests can be used to test for the sudden changes in financial market volatility. The Bai and Perron (2003), the CUSUM and the Inclán and Tiao (1994) tests are among the most popular in this regard. For example, the Bai and Perron (2003) test discloses the exact number of breaks and their corresponding dates of occurrence. This test

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however has a size distortion problem when heteroscedasticity is present in the time series data (Arouri et al., 2012). The CUSUM test is unable to provide the full information on the exact number of break points and their corresponding dates. On the other hand, the Inclán and Tiao (1994)'s ICSS test assumes the Gaussian distribution. Interestingly, the ICSS algorithm allows one to detect both the beginning and the ending of volatility regimes for the series. We describe this test below.

We suppose that $\varepsilon_t \sim N(0, h_t)$ where h_t denotes the unconditional variance in Eq. (1). For each interval j, the variance is given by τ_j for $j = 1, 2, \ldots, N_T$, where N_T is the total number of variance changes or jumps in the T observations. The set of those points of sudden variance shifts is given by $1 < K_1 < K_2 < \cdots < K_{N_T}$. The variance over the N_T intervals is defined as follows:

$$h_t = \begin{cases} \tau_0^2, & 1 < t < K_1 \\ \tau_1^2, & K_1 < t < K_2 \\ & \vdots \\ \tau_{N_T}^2 & K_{N_T} < t < T \end{cases}, \qquad (10)$$

In order to assess the number of changes or jumps in the variance and the time point for each variance shift, we apply the cumulative sum of squares procedure. The cumulative sum of the squared observations from the start of the series to the k[th] point in time is specified as follows:

$$C_k = \sum_{t=1}^{k} \varepsilon_t^2 \text{ , where } k = 1, 2, \ldots, T \text{ ,} \qquad (11)$$

The D_k statistic is given by

$$D_k = \left(\frac{C_k}{C_T} \right) - \frac{k}{T}, \text{where } D_0 = D_T = 0 \text{ ,} \qquad (12)$$

and C_T is the sum of squared residuals from the whole sample period.

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The D_k statistic will oscillate around zero if no changes or jumps in the variance occur but, if there is at least one sudden change in the variance of the series, the D_k statistic deviates from zero. These critical values define the upper and lower limits for the drifts. If the maximum of the absolute value of the statistic D_k is greater than the critical value, then the null hypothesis of no sudden change in variance is rejected. In this case, by letting k^* be the value at which $\max_k |D_k|$ is reached, and if $\max_k \sqrt{(T/2)}|D_k|$ exceeds the critical value, then k^* is taken as an estimate of the change or jump point. The term $\sqrt{(T/2)}$ is used to standardize the distribution.

The critical value of 1.358 is the 95th percentile of the asymptotic distribution of $\max_k \sqrt{(T/2)}|D_k|$. Therefore, the upper and lower boundaries can be established at ± 1.358 in the D_k plot. A change or jump point in variance is identified if D_k exceeds these boundaries. However, if the series harbors multiple change points, the D_k function alone will not be sufficiently powerful to detect the change points at different intervals. To overcome this shortcoming, Inclán and Tiao (1994) amended an algorithm that uses the function to search systematically for change points at different points in the series. This algorithm works by evaluating the D_k function over different time periods, and those periods are determined by the breakpoints, which are themselves identified by the D_k plot.

In this study, the original IT (1994) test is not appropriate and may reveal spurious regressions because the financial time-series under consideration exhibit stylized facts (e.g., asymmetry, leptokurticity and conditional heteroscedasticity). Given these drawbacks, we use the adjusted IT (AIT) test developed by Sanso et al. (2004), which is more flexible than the original IT test because it considers the fourth moment properties of the distributions and the

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conditional heteroscedasticity.[5] The statistical hypothesis test is expressed as follows: the null hypothesis of a constant unconditional variance of stock returns is tested against the alternative of presence of structural breaks in the unconditional variance.

The AIT empirical statistic, using a non-parametric adjustment based on Bartlett and Kernel, is given by

$$AIT = \sup_k \left| T^{-0.5} G_k \right| \quad , \tag{13}$$

where $G_k = \hat{\gamma}^{-0.5}\left[C_k - \left(\frac{k}{T}\right)C_T\right]$, $\hat{\gamma} = \hat{\delta} + 2\sum_{i=1}^{m}\left[1 - i(m+1)^{-1}\right]\hat{\delta}_i$, $\hat{\delta}_i = T^{-1}\sum_{t=i+1}^{k}\left(r_t^2 - \hat{\sigma}^2\right)\left(r_{t-1}^2 - \hat{\sigma}^2\right)$ and $\hat{\sigma}^2 = T^{-1}C_T$. The parameter m refers to a lag truncation parameter and is selected using the procedure in Newey and West (1994), and the other variables are defined earlier. The asymptotic distribution of the AIT statistic under general conditions is given by $\sup_l \left|W^*(l)\right|$, and the finite-sample critical values can be generated by simulations.[6] The 95th percentile critical value for the asymptotic distribution of AIT statistic is 1.4058.

3.3. Value at Risk (VaR) forecasting

VaRs have become the popular tool for measuring portfolio market risk. Several studies use this approach including Jorian (2007), Wu and Shieh (2007), Christoffersen (2009), Hammoudeh et al. (2011), and Hammoudeh et al. (2013). We estimate and compare the performance of the DCC-FIAPARCH model estimated under the three innovation distribution assumptions for the normal, Student-*t*, and skewed Student -*t* distributions. A

[5] The IT test is widely used by researchers to detect sudden changes in the volatility of financial time-series (see among others Aggrawal et al., 1999; Kang et al., 2011; Kumar and Maheswaran, 2013; Malik, 2003; Todea and Petrescu, 2012; Liu et al., 2014). Fewer studies have used the adjusted IT test including Arouri et al. (2012) and Charles and Darné (2014), Ewing and Malik (2010) and Vivian and Wohar (2012), among others.
[6] $W^*(l)=W(l) - lW(1)$is a Brownian bridge and W(l) is a Brownian motion.

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one-day-ahead VaR is calculated based on the results of the estimated conditional volatility models and the given distributions.

The VaRs for long and short trading positions can be specified for each of the three distribution assumptions. Under the normal distribution hypothesis, they are given by

$$VaR_{t,long} = \mu_t + z_\alpha \hat{\sigma}_t \tag{14}$$

$$VaR_{t,short} = \mu_t + z_{1-\alpha} \hat{\sigma}_t \tag{15}$$

Where μ_t and $\hat{\sigma}_t$ denote the conditional mean and variance forecasted at time $t-1$, respectively, and z_α is the left quantile at the $\alpha\%$ level for the normal distribution, while $z_{1-\alpha}$ is the right quantile at the $\alpha\%$ level for this distribution. While under the Student-t distribution hypothesis, the VaR is

$$VaR_{t,long} = \mu_t + st_\alpha(\upsilon)\hat{\sigma}_t \tag{16}$$

$$VaR_{t,short} = \mu_t + st_{1-\alpha}(\upsilon)\hat{\sigma}_t \tag{17}$$

where st_α is the left quantile at $\alpha\%$ for the Student-t distribution, while $st_{1-\alpha}(\upsilon)$ is the right quantile at $\alpha\%$ for this distribution. Finally, under the skewed Student-t distribution hypothesis, the VaR is

$$VaR_{t,long} = \mu_t + skst_\alpha(\upsilon,k)\hat{\sigma}_t \tag{18}$$

$$VaR_{t,short} = \mu_t + skst_{1-\alpha}(\upsilon,k)\hat{\sigma}_t \tag{19}$$

where $skst_\alpha(\upsilon,k)$ is the left quantile at $\alpha\%$ for the Skewed Student-t distribution, while $skst_{1-\alpha}(\upsilon,k)$ is the right quantile at $\alpha\%$ for this distribution.[7]

[7] The value of the parameter υ measures the degree of fat tails in the VaR density. If $\upsilon > 2$, the density has fat tails. The value of k determines the degree of asymmetry in the VaR density. If $k < 1$, the VaR for the long

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We calculate the VaR at the pre-specified significance level of $\alpha\%$ and then evaluate the performance by calculating the failure rate for both the left and right tails of the distribution in the sample return series. The failure rate, denoted f, is defined as the ratio of the number of times in which positive (negative) returns go beyond (below) the forecasted VaR to the sample size. Following Giot and Laurent (2003), testing the accuracy of the model is equivalent to testing the hypothesis $\begin{cases} H_0 : f = \alpha \\ H_1 : f \neq \alpha \end{cases}$. If the VaR model is correctly specified, then when the failure rate is close to the pre-determined VaR level $\alpha\%$, it indicates that VaR is computed efficiently. The Kupiec (1995) LR test statistic is expressed as follows:

$$LR = -2\ln\left[(1-\alpha)^{N-x}\alpha^{x}\right] + 2\ln\left[(1-f)^{N-x}\hat{f}^{x}\right] , \quad (20)$$

where $\hat{f} = \frac{x}{N}$ and x is the number of observations exceeding the forecasted VaR and N is the sample size.

4. Data and summary statistics

4.1. Data

Our analysis is based on the daily closing spot price index data for the pool of the five BRICS markets namely Brazil, Russia, India, China, and South Africa, as well as for one major developed market which is the S&P 500 representing the U.S. stock market. Among the emerging markets, the growth of the BRICS stock markets is fashionable.

The S&P 500 index is widely regarded as the best single gauge of the U.S. large cap equities. The index includes 500 leading companies and captures approximately about 80% of the coverage of the available market capitalization. Thus, it is the most representative index in

trading positions will be larger for the same conditional variance than the VaR for the short trading positions. When $k > 1$, the opposite holds true.

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the U.S. and has dethroned the Dow Jones Industrial Average. The S&P 500 also represents the most liquid stock index for the largest 500 U.S. firms and its value reflects the market capitalization of companies included in the index. The S&P 500 detects however broad movements in stock markets during economic expansion/recession periods. It is particularly interesting to investigate the cross-market linkages between the U.S. and BRICS stock markets. Krishnamurthy (2010) documents that the adjustment in the S&P 500 occurs with a delay, compared to the burst of the crisis on the debt and mortgages markets.

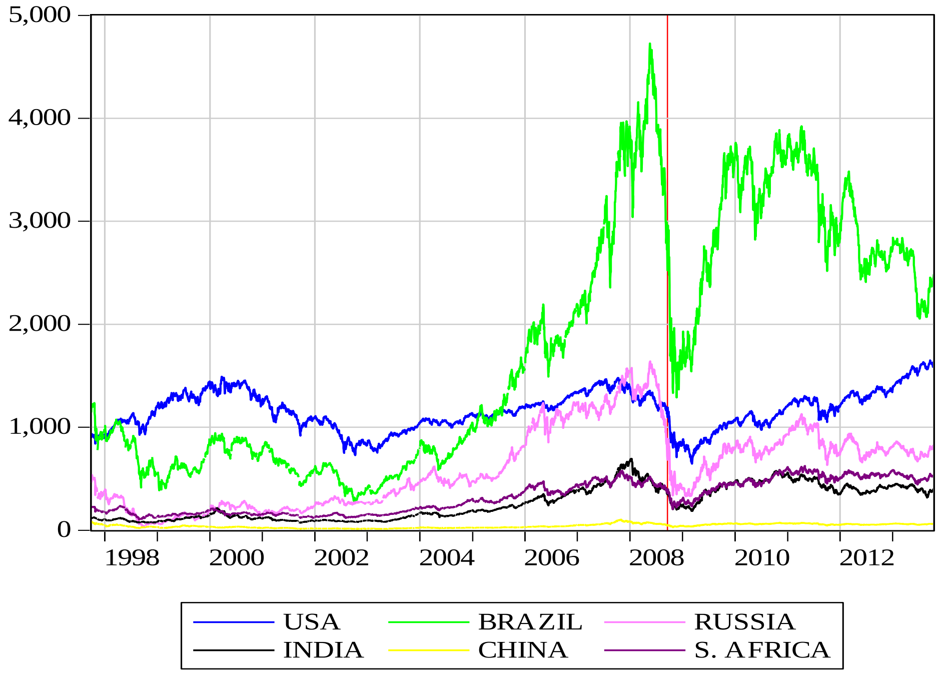

Fig. 1. Time-paths of the daily indices for the U.S. and BRICS stock markets

The study spans the period from September 29, 1997 to October 14, 2013. The data for BRICS and US market indices are obtained from the MSCI database. These indices are quoted in U.S. dollars in order to have conformity and to avoid the effects of local inflation and national currency fluctuations on the indexes, as indicated by Bekaert and Harvey (1995) and Dimitriou et al. (2013).

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Figure 1 illustrates the dynamics of the daily U.S. and BRICS indices over the sample period. The red dotted line indicates the break date September 15, 2008 which corresponds to the Lehman Brothers collapse. This figure displays a significant decline in the S&P 500 index as well as in each BRICS stock index since the bankruptcy of the Lehman Brothers. This date is selected as break point of the GFC.[8]

4.2. Summary statistics

We calculate the continuously compounded daily returns by taking the difference in the logarithms of two consecutive prices of a series. The descriptive statistics and the results of the statistical tests of the daily returns for the BRICS and the U.S. markets are presented in Table 1.

Table 1
Statistical properties: daily returns of U.S. and BRICS stock indices.

	U.S.	Brazil	Russia	India	China	S. Africa
Mean	0.0001	0.0002	0.0001	0.0003	0.00006	0.0002
Max.	0.1104	0.1733	0.2422	0.1948	0.1404	0.1235
Min.	-0.095	-0.1832	-0.2809	-0.1209	-0.1444	-0.1357
Std. dev.	0.0131	0.0242	0.0310	0.0185	0.0206	0.0187
Skewness	-0.2223	-0.2626	-0.4274	-0.1114	0.0350	-0.4215
Kurtosis	10.286	10.547	14.637	9.5496	7.8193	7.6858
Jarque-Bera	9022.45^{+}	9689.4^{+}	23052^{+}	7270.7^{+}	3932.8^{+}	3837.5^{+}
Q(20)	80.698^{+}	81.325^{+}	80.643^{+}	80.628^{+}	77.581^{+}	59.548^{+}
$Q^2(20)$	4871.3^{+}	3221.3^{+}	2256.3^{+}	860.66^{+}	2401.1^{+}	2652.9^{+}
ADF	-68.558^{+}	-59.168^{+}	-59.439^{+}	-59.508^{+}	-57.989^{+}	-59.969^{+}
PP	-69.317^{+}	-59.027^{+}	-59.458^{+}	-59.819^{+}	-57.854^{+}	-59.859^{+}
KPSS	0.0963	0.1533	0.1106	0.0912	0.3889	0.0966
ARCH-LM (10)	124.06^{+}	109.39^{+}	73.756^{+}	32.031^{+}	70.501^{+}	73.046^{+}

Notes: Q(20) refers to the Ljung-Box test for autocorrelation, respectively. ADF, PP and KPSS are the empirical statistics of the Augmented Dickey-Fuller (1979), and the Phillips-Perron (1988) unit root tests, and the Kwiatkowski et al. (1992) stationarity test, respectively. ARCH-LM(10) test of Engle (1982) is to check the presence of ARCH effects. $^{+}$ denotes the rejection of the null hypotheses of normality, no autocorrelation, unit root, non-stationarity, and conditional homoscedasticity at the 1% significance level.

The results reveal that the highest average return is for the Indian index, while volatility (as measured by the standard deviation) is the highest for the Russian index, thereby indicating that investment in the Russian stock market may prove to be more risky than in the

[8] More details are provided in Subsection 5.2.

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other BRICS markets. Russia is the largest borrower on the global debt market and its revenues from its hydrocarbon exports account for 45% of its government budget. Conversely, the U.S. market is found to have the lowest volatility.

The skewness and kurtosis results, along with the Jarque-Bera test for normality, indicate that the daily returns for both the BRICS and the U.S. markets are asymmetric, fat-tailed and high-peaked than the Gaussian distribution. These results are consistent with the GARCH effects. Moreover, based on the ARCH effects of Engle (1982), we strongly reject the null hypothesis of no ARCH effects. As shown in Table 1, the results of the Ljung-Box test statistics of the residuals, Q(20), and the squared residuals, $Q^2(20)$, reject the null hypothesis of no serial correlation. The return series for all considered markets are also found to be stationary based on two unit root tests (i.e., the ADF and PP) and a stationarity test (KPSS).

Table 2
Unconditional correlations of sample returns among the U.S. and BRICS stock returns

	U.S.	Brazil	Russia	India	China	S. Africa
U.S.	1.0000					
Brazil	0.5559	1.0000				
Russia	0.2862	0.3899	1.0000			
India	0.1877	0.2715	0.3084	1.0000		
China	0.1581	0.2849	0.3178	0.4098	1.0000	
S. Africa	0.3238	0.5234	0.5234	0.3730	0.4016	1.0000

To justify the use of FIAPARCH model, we carry out the Pearson correlations, the pairwise Granger causality tests between the U.S. and BRICS market returns and the conventional long memory (LM) tests for these returns. Furthermore, the Pearson correlation results which are provided in Table 2 show evidence of low correlations between the BRICS and the U.S. markets. The lowest correlation coefficients are clearly observed for China and the United States. For a while, China did not allow foreigners to invest in its A-shares.

To examine the presence of the LM property for the different BRICS and the United States stock markets, we run a battery of LM tests on those markets. Indeed, we consider four

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kinds of procedures of the LM test, namely the Hurst-Mandelbrot R/S test, Lo's modified R/S test, the Gaussian semi-parametric (GSP) test of Robinson and Henry (1999), and the GPH test of Geweke and Porter-Hudak (1983).[9] Table 3 summarizes the results of the LM tests for all return and squared return series (as a proxy variable of volatility) for the U.S. and BRICS markets, respectively. For the return series, the results reject evidence of the LM property. The evidence for the squared returns is totally different from those of the returns. In fact, the LM property is found to be highly significant (at the 1% level of significance) for all squared return series, whatever the applied LM tests under consideration are. Overall, the squared returns may be governed by a fractionally integrated model. The FIAPARCH specification is thus suitable for capturing these stylized facts (asymmetry, long memory, heteroscedasticity).

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[9] In the case of the Hurst-Mandelbrot R/S and Lo's modified R/S tests, the Hurst exponent (*H*) is calculated using the R/S statistic. If $H = 0.5$, then this exponent indicates a random walk process which means short memory. If $0 \leq H \leq 0.5$, it suggests that the series is anti-persistent process (i.e., a long-range negative dependence) but if $0.5 < H \leq 1$, the series is a persistent process. To test for the statistical significance of the H estimates, we use the t-test statistic, where the null hypothesis is $H_0 : H = 0.5$ and the alternative hypothesis is $H_1 : H \neq 0.5$. On the other hand, both the GSP and GPH methods test the null hypothesis $H_0 : d = 0$ versus $H_1 : d \neq 0$ using the t-test statistic. If $d = 0$, the series is a random walk or has a short-memory process; if $-0.5 < d < 0$, it is an anti-persistent process; if $0 < d < 0.5$, it has a long memory; and if $0.5 < d < 1$, it is non-stationary. In order to ensure the robustness of the GSP and GPH tests, this paper uses several choices of the low-frequency ordinates. These choices regarding the number of low-frequency ordinates, n, vary with the sample size T and are established in terms of $n = T^{\alpha}$ with α = {0.45, 0.50, 0.55,and 0.6}.

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Table 3
Long memory tests for returns and squared returns of the U.S. and BRICS markets

	Returns						Squared Returns					
	U.S.	Brazil	Russia	India	China	S. Africa	U.S.	Brazil	Russia	India	China	S. Africa
Panel A: Hurst-Mandelbrot R/S test												
Test statistic	1.3974	1.6642	1.8420	1.5351	1.6424	1.0888	4.8879***	3.5799***	5.3297***	4.2538***	4.4883***	4.4703***
Panel B: Lo's modified R/S test												
Test statistic $(q=1)$	1.4514	1.6059	1.7813	1.4853	1.5703	1.0573	4.4535***	3.2862***	4.6326***	3.9615***	4.0554***	4.0368***
Test statistic $(q=5)$	1.5479	1.6235	1.7492	1.4334	1.5340	1.0679	3.2478***	2.4092***	3.7003***	3.3172***	3.0601***	3.1555***
Panel C: GSP test												
$d\ (m=T/4)$	-0.0519***	-0.0075	0.0234	0.0238	0.0218	-0.0197	0.2755***	0.2905***	0.2022***	0.1663***	0.2771***	0.2088***
	(0.0156)	(0.0156)	(0.0156)	(0.0156)	(0.0156)	(0.0156)	(0.0156)	(0.0156)	(0.0156)	(0.0156)	(0.0156)	(0.0156)
$d\ (m=T/16)$	0.0191	0.0438	0.0820***	0.1073***	0.0565	0.0216	0.5959***	0.5052***	0.4142***	0.2950***	0.3796***	0.4490***
	(0.0313)	(0.0313)	(0.0313)	(0.0313)	(0.0313)	(0.0313)	(0.0313)	(0.0313)	(0.0313)	(0.0313)	(0.0313)	(0.0313)
$d\ (m=T/32)$	0.0180	0.0651	0.1247	0.0336	0.0822	0.0171	0.5577***	0.4144***	0.4594***	0.3091***	0.4139***	0.4656***
	(0.0443)	(0.0443)	(0.0443)	(0.0443)	(0.0443)	(0.0443)	(0.0443)	(0.0443)	(0.0443)	(0.0443)	(0.0443)	(0.0443)
$d\ (m=T/64)$	0.0237	0.0387	0.0383	0.0481	0.0385	-0.0237	0.4824***	0.3233***	0.4008***	0.2919***	0.3750***	0.4157***
	(0.0629)	(0.0629)	(0.0629)	(0.0629)	(0.0629)	(0.0629)	(0.0625)	(0.0629)	(0.0629)	(0.0629)	(0.0629)	(0.0629)
Panel D: GPH test												
$d\ (m=T^{0.45})$	0.1970	0.1341	0.1238	0.0516	0.0266	-0.0475	0.3021***	0.1480	0.3082***	0.2680***	0.2813***	0.3269***
	(0.1142)	(0.1142)	(0.1142)	(0.1142)	(0.1142)	(0.1142)	(0.1142)	(0.1142)	(0.1142)	(0.1172)	(0.1142)	(0.1142)
$d\ (m=T^{0.5})$	0.1152	0.0295	-0.0012	0.1051	0.0476	-0.0113	0.4560***	0.2751***	0.3433***	0.2420***	0.3182***	0.4468***
	(0.0893)	(0.0893)	(0.0893)	(0.0893)	(0.0893)	(0.0893)	(0.0893)	(0.0893)	(0.0893)	(0.0909)	(0.0899)	(0.0901)
$d\ (m=T^{0.55})$	0.1052	0.0771	0.0676	0.0851	0.1068	0.0664	0.5373***	0.3615***	0.4568***	0.2692***	0.3595***	0.4807***
	(0.0710)	(0.0710)	(0.0710)	(0.0710)	(0.0710)	(0.0710)	(0.0721)	(0.0710)	(0.0710)	(0.0726)	(0.0711)	(0.0711)
$d\ (m=T^{0.6})$	0.0803	0.0491	0.1055	0.1237	0.0940	0.0494	0.4774***	0.3621***	0.4063***	0.2920***	0.3849***	0.4467***
	(0.0564)	(0.0564)	(0.0564)	(0.0564)	(0.0564)	(0.0564)	(0.0582)	(0.0565)	(0.0564)	(0.0569)	(0.0564)	(0.0570)

Notes: The critical values of the Hurst-Mandelbrot R/S test and Lo's modified R/S analysis are 2.098 at the 1% significance level, respectively. The numbers in parentheses are the standard deviation of the estimates. "q" in Lo's modified R/S test is the number of lag of autocorrelation. (m) denotes the bandwidth for the GSP and the GPH tests. The asterisk *** indicates the significance level at 1%.

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Table 4
Estimation of the bivariate AR(1)-FIAPARCH(1,d,1)-DCC model (U.S.-BRICS)

	U.S.-Brazil		U.S.-Russia		U.S.-India		U.S.-China		U.S.-South Africa	
	U.S.	Brazil	U.S.	Russia	U.S.	India	U.S.	China	U.S.	S. Africa
Panel A: Estimates of the AR(1)-FIAPARCH model										
Const.(M)	0.0001	0.0000	0.0001	0.0001	0.0001	0.0007**	0.0001	0.0001	0.00001	0.0003
	(0.0001)	(0.0003)	(0.0001)	(0.0003)	(0.0001)	(0.0003)	(0.0001)	(0.0003)	(0.0002)	(0.0003)
AR(1)	-0.0333**	0.1143***	-0.0333**	0.0667***	-0.0333***	0.0754***	-0.0333**	0.0902***	-0.0333**	0.0623***
	(0.0149)	(0.0178)	(0.0149)	(0.0170)	(0.0149)	(0.0194)	(0.0149)	(0.0161)	(0.0149)	(0.0163)
Const. (V)	0.0000	0.0005	0.0003	0.0003	0.0003	0.0003	0.0003	0.0003	0.0003	0.0008
	(0.0001)	(0.0003)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0006)
d-Figarch	0.3172***	0.3139***	0.3172***	0.3681***	0.3172***	0.3787***	0.3172***	0.4179***	0.3172***	0.3416***
	(0.0628)	(0.0482)	(0.0628)	(0.0632)	(0.0628)	(0.1010)	(0.0628)	(0.0651)	(0.0628)	(0.0557)
Arch	0.1555	0.0903	0.1555	0.1190	0.1555	0.1822***	0.1555	0.2569***	0.1555	0.2453***
	(0.0991)	(0.0873)	(0.0992)	(0.0778)	(0.0992)	(0.0449)	(0.0992)	(0.0560)	(0.0992)	(0.0691)
Garch	0.4277***	0.3243***	0.4277***	0.3724***	0.4277***	0.4788***	0.4277***	0.5766***	0.4277***	0.5008***
	(0.1469)	(0.0980)	(0.1469)	(0.1051)	(0.1469)	(0.0831)	(0.1469)	(0.0860)	(0.1469)	(0.0874)
APARCH	0.9996***	0.6483***	0.9996***	0.2494***	0.9996***	0.4752***	0.9996***	0.3002***	0.9996***	0.6955***
(Gamma)	(0.0028)	(0.1745)	(0.0027)	(0.0623)	(0.0027)	(0.1436)	(0.0027)	(0.0616)	(0.0027)	(0.1486)
APARCH	1.2764***	1.4034***	1.2764***	1.8742***	1.2764***	1.4298***	1.2764***	1.7990***	1.2764***	1.2117***
(Delta)	(0.1027)	(0.1328)	(0.1027)	(0.0910)	(0.1027)	(0.1288)	(0.1028)	(0.1200)	(0.1027)	(0.1511)
Panel B: Estimates of the DCC model										
Average	0.5562***		0.3017***		0.1542***		0.1497***		0.3157***	
CORij	(0.0616)		(0.0250)		(0.0501)		(0.0159)		(0.1235)	
k_1	0.0185***		0.0074***		0.0045***		0.0030		0.0062***	
	(0.0054)		(0.0018)		(0.0013)		(0.0018)		(0.0018)	
k_2	0.9792***		0.9925***		0.9948***		0.9959***		0.9932***	
	(0.0070)		(0.0019)		(0.0017)		(0.0024)		(0.0020)	
Panel C: Diagnostic Tests										
Q(20)	35.784	27.335	41.694	18.835	33.297	36.489	38.144	35.359	42.306	19.980
	[0.0163]	[0.1260]	[0.0030]	[0.5325]	[0.0312]	[0.0134]	[0.0085]	[0.0182]	[0.0025]	[0.4591]
$Q^2(20)$	20.360	13.996	14.362	12.528	22.441	9.5786	21.735	14.256	17.432	15.989
	[0.4355]	[0.8306]	[0.8116]	[0.8966]	[0.3170]	[0.9751]	[0.3550]	[0.8172]	[0.6247]	[0.7172]

Notes: Q(20) and $Q^2(20)$ are the Ljung-Box test statistics applied to the standard residuals and the squared standardized residuals, respectively. The asterisks ** and *** indicate significance at the 5% and 1% levels, respectively. The p-values are in brackets and the standard errors are in parentheses.

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5. Empirical results and implications

This section discusses the results of the estimation for the full sample period, the structural breaks, and the effects of the GFC on the linkages among the U.S. and BRICS stock markets and the VaR analysis.

5.1 Estimation for the full sample period

Table 4 presents, under the Student-t distributed innovations, the full sample estimation results of the bivariate DCC-FIAPARCH$(1,d,1)$ model between the BRICS and the U.S. stock markets.[10] The lag order $(1,d,1)$ is chosen by using the Akaike information criteria (AIC) and the Schwarz information criteria (SIC). The parameter of mean equation (AR(1)) is positive and statistically significant at the 1% level for all cases, indicating that the past information set is instantaneously and rapidly embodied in the current stock indices for the U.S. and BRICS markets. Moreover, the leverage effect coefficient (Gamma) is positive and significant for the five emerging markets, indicating that the volatility of the BRICS stock markets is asymmetric. This result shows that the negative shocks have more impacts on the conditional volatility than the negative shocks for the same magnitude. This is consistent with the work of Dimitriou et al. (2013). On the other hand, the fractional integrated coefficient (d) is highly significant for all markets considered, revealing a high level of persistence.

[10] The estimation of the bivariate AR(1)-FIAPARCH(1,*d*,1) -DCC model with the SBs for the U.S.-BRICS pair is not reported here for a space constraint to show their lack of credibility. They however can be available upon request. In the case of including the SB over the sample period in the FIAPARCH model, which was generated from conducting the modified ICSS test on the unconditional volatility, we find no difference in the size of parameter *d* with/without the SB. Moreover, the AR(1) coefficients become insignificant. Surprisingly, all DCC estimates also become insignificant. In addition, we know based on the previous literature that if structural changes are ignored in the GARCH estimation, volatility persistence is generally overestimated. However, we find that in our case of including the SB generated from conducting the ICSS test on the AR(1)-FIAPARCH(1,*d*,1) -DCC, the values of the GARCH parameter rise after including SB. This result is not in line with existing studies (e.g., Ewing and Malik, 2005; Hammoudeh and Li, 2008; Mensi, et al, 2014). Having said that, the analysis we have followed in our study is more in step with the literature and also makes more sense. Thus, it makes no sense to conduct more work on making more use of the SBs generated from the conditional volatility model under consideration.

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Among the BRICS markets, the higher parameter is addressed for China with the U.S. stock market.

Panel B of Table 4 reports the estimates of the dynamic conditional correlation model (DCC). The ARCH effect (Alpha) is positive and significant for all stock market pairs, except for one pair (i.e., U.S.-China), underlying the importance of shocks between the U.S. and the BRICS markets. This implies that the BRICS markets are not able to act as a hedge or a safe haven for the U.S. market. For the GARCH effects (Beta), the parameters are significant and very close to one for all cases, confirming the higher persistence of volatility between the U.S. and the BRICS. In sum, the significance of the fractionally integrated parameters, k_1 and k_2, justifies the appropriateness of the FIAPARCH model. Specifically, the highest average conditional correlation is between the U.S. and Brazil markets with a value of 0.5562, while the lowest one is between the U.S. and China with a value of 0.1497. The U.S. neighborhood effect, openness to foreign investors and the lower number of structural breaks, as can be seen in the following subsection, apply more to Brazil than China when it comes to relationships with the United States. According to the diagnostic tests (Panel C), the Ljung-Box test statistics for the standard residuals and squared standardized residuals do not reject the null hypothesis of no serial correlation, providing evidence of no misspecification of our model.

5.2 Structural breaks

Whether structural breaks exist or not have important implications on the estimation results of our study. If they are present, the linkages between the US and BRICS stock markets may experience different phases of dynamics. Fig. 2 displays the return behavior of the six MSCI indices under consideration and points out the points of sudden changes in the return dynamics of those indices, particularly during the most severe periods of the global financial crisis. For this purpose, we use the adjusted ICSS algorithm to examine the extent of

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structural breaks. Our focus is on the structural breaks that occurred in the dynamics of the US stock market returns because this country plays a crucial role in the international financial system and its 2007 subprime crisis has led to the global financial crisis 2008-2009. Table 5 shows the seven structural breakpoints in the unconditional variance of the U.S. stock market. We also detect ten sudden changes for the Brazil, eleven for the Russia and thirteen for the rest of the emerging BRICS stock markets.[11] In general, important political, social and economic events at the local, regional and global levels such as country-specific economic situations, the 1997-1998 Asian financial crisis, the 2001 terrorist attack, the Gulf war, the 2008-2009 global financial crisis, and the Arab Spring stand behind the regime shifts in volatility for the U.S. and BRICS stock markets. Aggarwal et al., 1999) examine the sudden changes in the volatility of emerging markets and find that structural breaks are related to local political, social and economic events (i.e., the Mexican peso crisis, hyperinflation in Latin America, etc.), while the only global significant event detected is the 1987 October stock market crash. Hammoudeh and Li (2008) conclude that the events give rise to sudden changes are rather global than local ones.

[11] The results for the BRICS markets can be made entirely available upon request to the corresponding author. Further, we carry out the modified ICSS test based on the standardized residuals of the conditional volatility model and the results reveal four out of six countries have no SBs. The other two countries have one SB each, but the dates do not correspond to those of the GFC or major economic events.

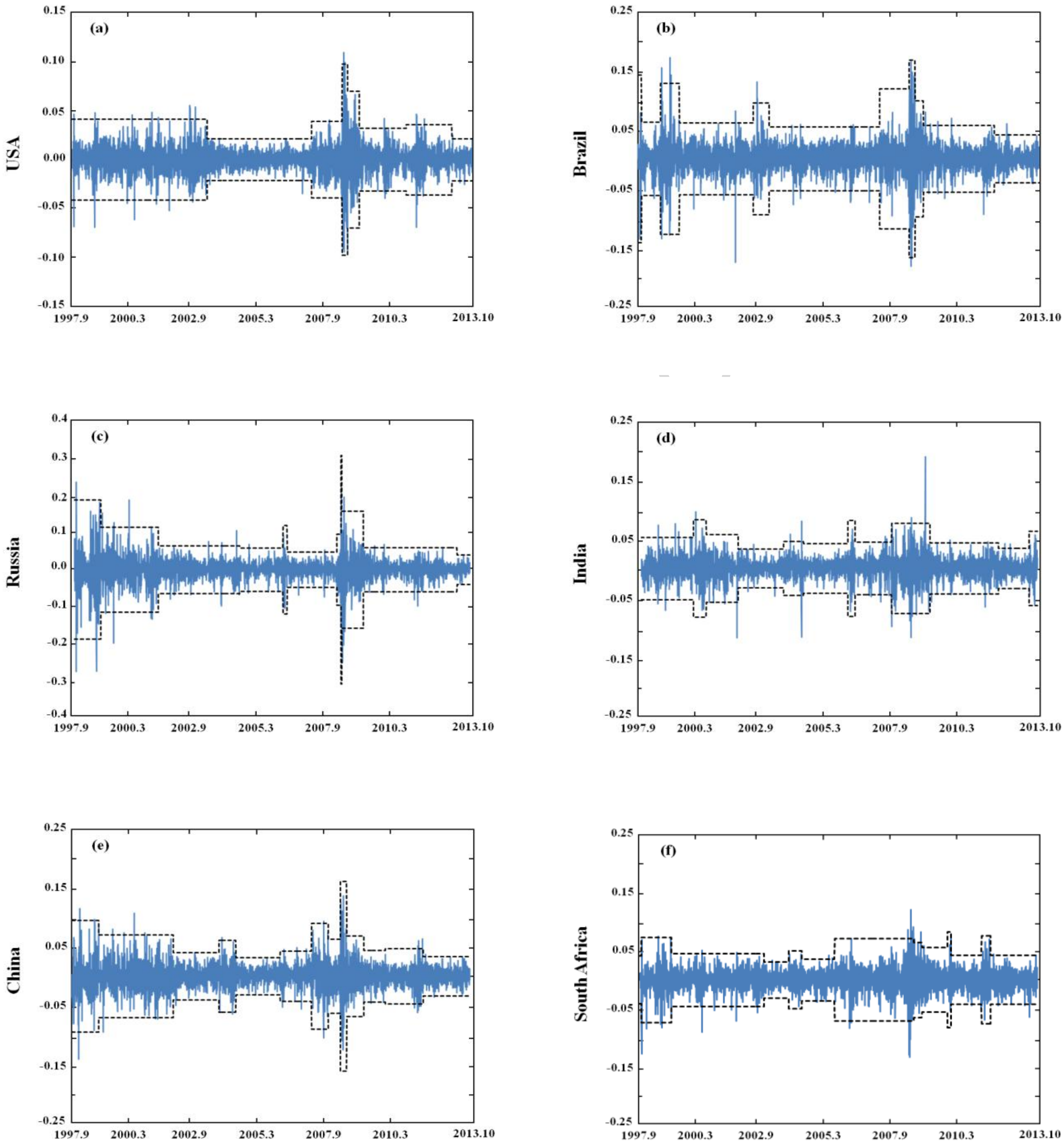

Fig. 2. Sudden changes in the return dynamics of the six MSCI indices

Notes: The bands (defined by dotted lines) are at ± 3 standard deviations around where structural changes points (dates) are estimated by the adjusted ICSS algorithm.

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Table 5.
Results of the structural break test applied to the US stock market

Number of breaks	Break dates	Possible corresponding events
7	04/28/2003	Gulf war
	07/09/2007	U.S. initial financial turmoil
	09/15/2008	**Lehman Brothers collapse**
	12/01/2008	Global financial crisis
	05/18/2009	Bull rally after global financial crisis
	03/14/2011	The Eurozone crisis enters into a new phase with some of the toughest austerity measure. Fitch and Standard & Poor's cut their ratings of Portuguese sovereign debt on March 15, 2011.
	12/20/2011	Strengthening of recovery

Notes: The structural break tests are conducted by the modified ICSS algorithm.

Another important finding from the structural break tests is that the common unexpected event for our sample markets is the globally identified Lehman Brothers collapse which took place on September 15, 2008. Indeed, stock markets in Brazil, Russia and the United States exhibited a structural break on September 15, 2008. The Chinese stock market is exposed to a structural break on September 16, 2008. While stock markets in India and South African did not display structural breaks around this "Lehman" event, they have several structural changes in 2008 and 2009. Hence, we can consider the 15th of September 2008 as a break point in order to identify the GFC occurrence and divide the full sample period into pre- and post-crisis periods. The pre-crisis period spans the period September 29, 1997 to September 15, 2008, while the post-crisis period ranges from September 16, 2008 until the end of the sample.

5.3. The effects of GFC on the linkages among the U.S. and BRICS stock markets

Tables 6 and 7 show the estimation results of the bivariate AR(1)-DCC-FIAPARCH $(1, d, 1)$ between the U.S. and each of BRICS stock markets before and after the GFC, respectively. Comparatively, the results provide evidence that the volatility of the index returns exhibits an LM behavior, indicating that the variance of returns of the series can be specified by a mean-reverting, fractionally integrated process. Additionally, the results also show that the LM parameter increases after the bankruptcy of Lehman Brothers, except for

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the Chinese stock markets, implying that the future volatility is more predictable due to the dependence of future volatility on its past realizations after this major financial crisis. For China, the LM coefficient declines from 0.3477 to 0.2605, indicating decreasing in volatility persistence in the Chinese stock market. Consistent with previous studies (e.g., Dimitriou et al., 2013, among others), the impacts of shocks on the conditional volatility in the U.S. and BRICS markets are severely affected by the GFC.

Furthermore, the volatility process is highly persistent after the GFC for all pairs, again with the exception of the Chinese stock markets for which both the ARCH and GARCH parameters decrease significantly after this crisis. For all considered stock markets (except for the Russian market), the asymmetry parameter is statistically significant and positive, indicating the presence of a leverage effect in stock markets. The leverage effect increases only for the China and South Africa stock markets and decreases for the rest of markets after the crisis.

Regarding the average correlations, we find that the comovement parameter between U.S. and BRICS stock markets (with the exception of the Russian market) is statistically significant after the GFC, supporting the recoupling hypothesis. For the Russian case, the average dependence is insignificant, sign of isolation (decoupling) between the U.S. and Russian markets since the Lehman Brothers collapse. Russia exports 80% of gas exports to Europe. On the other hand, its trade with the U.S. is about 1% of the latter's GDP. On the other hand, we conclude that the rise in dynamic correlations among the U.S. and BRICS (except for Russia) shows evidence of strengthening linkages. Ahmad et al. (2013) find similar result since the BRICS are founded to be strongly hit by the European contagion shock resulted from the Eurozone crisis. Our findings are not consistent with those of Xu and Hamori (2012), who find that the international transmission of stock prices between the U.S.

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and the BRICs was significantly weakened in both the mean and variance after the recent financial crisis period.

In sum, the shift behavior of the investor risk appetite during the economic expansion and recession periods. Moreover, the recent global financial meltdown has had a damaging effect for asset allocation of investors and portfolio managers. It hinders the ability of financial markets to allocate their assets optimally. We address this objective of this study by computing the VaR which is the topic of the next subsection.

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Table 6.
Estimation of the bivariate AR(1)-DCC-FIAPARCH(1,*d*,1) model (U.S.-BRICS) in the pre-crisis period

	U.S.-Brazil		U.S.-Russia		U.S.-India		U.S.-China		U.S.-South Africa	
	U.S.	Brazil	U.S.	Russia	U.S.	India	U.S.	China	U.S.	S. Africa
Panel A: Conditional mean equation										
Const.(M)	-0.00003	0.00028	-0.00003	0.00079*	-0.00003	0.00105***	-0.00003	0.00032	-0.00003	0.00054
	(0.00017)	(0.00041)	(0.00017)	(0.00043)	(0.00017)	(0.00034)	(0.00017)	(0.00037)	(0.00017)	(0.00034)
AR(1)	-0.0382**	0.1236***	-0.0382**	0.0678***	-0.0382**	0.0895***	-0.0382**	0.1190***	-0.0382**	0.0828***
	(0.0188)	(0.0198)	(0.0188)	(0.0212)	(0.0188)	(0.0227)	(0.0188)	(0.0203)	(0.0188)	(0.0199)
Const. (V)	0.00007	0.00047	0.00007	0.00005	0.00007	0.00006	0.00007	0.000002	0.00007	0.00017
	(0.00010)	(0.00034)	(0.00010)	(0.00004)	(0.00010)	(0.00007)	(0.00010)	(0.000002)	(0.00010)	(0.00018)
d-FIGARCH	0.1770***	0.2776***	0.1770***	0.3361***	0.1770***	0.3190***	0.1770***	0.3477***	0.1770***	0.3014***
	(0.0365)	(0.0449)	(0.0365)	(0.0771)	(0.0365)	(0.0923)	(0.0365)	(0.0892)	(0.0365)	(0.0555)
ARCH	-0.2348	0.0149	-0.2348	0.02278	-0.2348	0.1220**	-0.2348	0.3070***	-0.2348	0.1532
	(0.2561)	(0.1227)	(0.2561)	(0.0896)	(0.2561)	(0.0597)	(0.2561)	(0.0897)	(0.2561)	(0.1210)
GARCH	-0.0855	0.1986	-0.0855	0.2179*	-0.0855	0.3397***	-0.0855	0.5280***	-0.0855	0.3576***
	(0.2765)	(0.1348)	(0.2765)	(0.1191)	(0.2765)	(0.0951)	(0.2765)	(0.1364)	(0.2765)	(0.1428)
APARCH	0.9891***	0.8440***	0.9891***	0.2315***	0.9891***	0.5438***	0.9891***	0.2645***	0.9891***	0.6521***
(Gamma)	(0.0331)	(0.2182)	(0.0331)	(0.0695)	(0.0331)	(0.1984)	(0.0331)	(0.0665)	(0.0331)	(0.1792)
APARCH	1.5927***	1.0494***	1.5927***	1.9151***	1.5927***	1.3416***	1.5927***	1.9364***	1.5927***	1.1410***
(Delta)	(0.1740)	(0.1634)	(0.1740)	(0.1162)	(0.1740)	(0.1932)	(0.1740)	(0.1910)	(0.1740)	(0.2360)
Panel B: Estimates of the DCC equation										
Average	0.5172***		0.2047***		0.0791***		0.1091***		0.2387***	
CORij	(0.0363)		(0.0256)		(0.0241)		(0.0206)		(0.0190)	
k_1	0.0229***		0.0000		0.0000		0.0045		0.0000	
	(0.0087)		(0.0000)		(0.0000)		(0.0097)		(0.0000)	
k_2	0.9617***		0.8104		0.8303		0.8438***		0.8527***	
	(0.0203)		(1.0386)		(13.658)		(0.1020)		(0.2305)	
Panel C: Diagnostic tests										
Q(20)	28.150	27.356	31.299	18.566	29.903	28.496	32.628	35.656	32.724	20.796
	[0.1059]	[0.1255]	[0.0513]	[0.5501]	[0.0714]	[0.0981]	[0.0370]	[0.0168]	[0.0361]	[0.4092]
$Q^2(20)$	23.443	13.132	16.141	12.921	17.565	5.9452	18.394	12.241	20.387	10.263
	[0.2675]	[0.8716]	[0.7077]	[0.8807]	[0.6159]	[0.9989]	[0.5614]	[0.9075]	[0.4339]	[0.9631]

Notes: see notes of Table 5.

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Table 7
Estimation of the bivariate AR(1)-DCC-FIAPARCH(1,*d*,1) model (U.S.-BRICS) in the post-crisis period

	U.S.-Brazil		U.S.-Russia		U.S.-India		USA-China		U.S.-South Africa	
	U.S.	Brazil	U.S.	Russia	U.S.	India	U.S.	China	U.S.	S. Africa
Panel A: Conditional mean equation										
Const.(M)	0.00034	-0.00054	0.00034	0.00016	0.00034	-0.00002	0.00034	-0.00019	0.00034	-0.00035
	(0.00024)	(0.00047)	(0.00024)	(0.00053)	(0.00024)	(0.00043)	(0.00024)	(0.00037)	(0.00024)	(0.00043)
AR(1)	-0.0472	0.0735***	-0.0472	0.0658**	-0.0472	0.0373	-0.0472	0.02296	-0.0472	-0.00023
	(0.0276)	(0.0286)	(0.0276)	(0.0269)	(0.0276)	(0.0311)	(0.0276)	(0.02545)	(0.0276)	(0.02719)
Const. (V)	0.00002	0.00003	0.00002	0.000007	0.00002	0.00003	0.00002	0.000018	0.00002	0.00001
	(0.00001)	(0.00004)	(0.00001)	(0.00001)	(0.00001)	(0.00004)	(0.00001)	(0.000027)	(0.00001)	(0.00001)
d-FIGARCH	0.4616***	0.3266***	0.4616***	0.5044*	0.4616***	0.5949***	0.4616***	0.2605***	0.4616***	0.3528***
	(0.0970)	(0.0984)	(0.0970)	(0.2586)	(0.0970)	(0.1076)	(0.0970)	(0.0963)	(0.0970)	(0.0757)
ARCH	0.1896***	0.1772**	0.1896***	0.1446*	0.1896***	0.1643*	0.1896***	0.1364	0.1896***	0.3139***
	(0.0496)	(0.0896)	(0.0496)	(0.0753)	(0.0496)	(0.0838)	(0.0496)	(0.1183)	(0.0496)	(0.0560)
GARCH	0.6022***	0.4661***	0.6022***	0.6344***	0.6022***	0.7366**	0.6022***	0.3746***	0.6022***	0.6061***
	(0.0837)	(0.1121)	(0.0837)	(0.2260)	(0.0837)	(0.0486)	(0.0837)	(0.1350)	(0.0837)	(0.0797)
APARCH	0.9815***	0.6691***	0.9815***	0.2459	0.9815***	0.3353*	0.9815***	0.6050**	0.9815***	0.9933***
(Gamma)	(0.1095)	(0.2497)	(0.1095)	(0.1600)	(0.1095)	(0.1835)	(0.1095)	(0.2790)	(0.1095)	(0.0539)
APARCH	1.2430***	1.6525***	1.2430***	1.9324***	1.2430***	1.6724***	1.2430***	1.7890***	1.2430***	1.3948***
(Delta)	(0.1006)	(0.1633)	(0.1006)	(0.2449)	(0.1006)	(0.2560)	(0.1006)	(0.1762)	(0.1006)	(0.1193)
Panel B: Estimates of the DCC equation										
Average	0.6944***		0.2543		0.3249***		0.2615***		0.5024***	
CORij	(0.0644)		(0.2136)		(0.0235)		(0.0284)		(0.0246)	
k_1	0.0172***		0.0130***		0.0000		0.0158		0.0593**	
	(0.0082)		(0.0048)		(0.0000)		(0.0306)		(0.0265)	
k_2	0.9765***		0.9869***		0.8231**		0.4290*		0.5250***	
	(0.0161)		(0.0047)		(0.3863)		(0.2607)		(0.1645)	
Panel C: Diagnostic Tests										
Q(20)	16.008	14.941	28.277	20.399	20.922	26.738	24.613	29.991	25.046	20.272
	[0.7161]	[0.7797]	[0.1029]	[0.4332]	[0.4016]	[0.1427]	[0.2166]	[0.0699]	[0.1996]	[0.4410]
$Q^2(20)$	14.267	19.773	12.892	38.888	17.864	9.9043	17.411	23.431	15.882	30.204
	[0.8166]	[0.4721]	[0.8819]	[0.0068]	[0.5963]	[0.9698]	[0.6261]	[0.2681]	[0.7238]	[0.0666]

Notes: see notes of Table 5.

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5.4. VaR forecasting analysis

For the six MSCI indices (U.S. and BRICS), we assess the performance of the normal, Student-t and skewed Student-t FIAPARCH $(1, d, 1)$ models for the in-sample and out-of sample VaR analysis, taking into account the long and short trading positions. We evaluate the VaR models at a significance level array of α, ranging from 0.05 to 0.0025, by computing the failure rate. The null hypothesis that the failure rate is equal to a pre specified quantile is tested against the alternative hypothesis that the failure rate exceeds the prescribed quantiles. The VaR models present a good performance if the null hypothesis is not rejected; otherwise these models give a poor performance.

The in-sample-VaR performance results under the alternative distribution modeling assumptions are reported in Tables 8-9 for both the short and long trading positions, respectively. The results fail to provide evidence of accurate performance of the FIAPARCH models with the normal and Student-t distributions for the two trading positions and regardless of the considered indices, except for the China case whose Student-t distribution FIAPARCH is accepted for the short trading positions and for long trading positions in several quantiles. On the other hand, the null hypothesis that the failure rate is equal to a pre-specified significance level of quantile $(f = \alpha)$, ranging from 0.05 to 0.0025, is not rejected for all indices and for the short and long trading positions when the skewed Student-t distributions is considered. Indeed, this model is able to explain the in-sample VaR performance by improving the predictive accuracy.

Based on these in-sample results, we conclude that the in-sample VaR models are mis-specified with the normal and Student-t distributions. More importantly, investors and portfolio risk managers can use the skewed Student-t FIAPARCH (1,d,1) model to compute the in-sample VaR, building an appropriate risk management strategy for portfolios involving both the U.S. and BRICS stock markets and eliminate the uncertainty in maximum losses. On

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the other hand, the density of the U.S. and BRICS stock return series exhibits skewed and fat-tailed features. The asymmetric long-memory model with the skewed Student-t distribution is suitable to model the volatility in these markets.

Following the analysis procedure used by Wu and Shieh (2007), we apply an iterative procedure by which the estimated model for the whole sample is estimated and then the predicted one-day-ahead VaR is compared for both the long and short trading positions. To conduct the out-of-sample VaR forecasting analysis, the last 1250 (5-year) observations of the entire sample are used. The models are re-estimated every 50 observations using a rolling regression approach.[12]

To assess the one-day-ahead forecasting performance of the FIAPARCH $(1, d, 1)$ model employing the innovations of three distributions, the out-of-sample VaR values are also examined. Tables 10-11 present the one-day ahead forecasting performance results by computing the failure rates and their corresponding Kupiec LR tests for both short and long trading positions, respectively. With a few exceptions, we find that the skewed Student-t distribution VaR model is more suitable to provide accurate volatility forecasting results for long and short trading positions for the U.S. and BRICS markets.

On the whole, the in-sample VaR estimates are generally similar to those of out-of-sample VaR. Moreover, in almost all cases the skewed Student-t FIAPARCH models outperform the other competing model specifications in modeling and forecasting the conditional volatility of the U.S. and BRICS stock markets, predicting critical loss more accurately than do the other models. The portfolio risk managers and investors should focus on this model to compute the VaRs.

[12] For more details, see Wu and Shieh (2007).

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Table 8.
The U.S. and BRICS in-sample VaR analysis (short trading positions case)

	U.S		Brazil		Russia		India		China		South Africa	
Quantile	Failure rate	Kupiec LRT	Failure rate	Kupiec LRT	Failure rate	Kupiec LRT	Failure rate	Kupiec LRT	Failure rate	Kupiec LRT	Failure rate	Kupiec LRT
FIAPARCH model – normal distribution												
0.9500	0.9586	6.7856 [0.009]	0.9621	13.610 [0.000]	0.9603	9.8807 [0.002]	0.9638	18.000 [0.000]	0.9552	2.3983 [0.121]	0.9589	7.1899 [0.007]
0.9750	0.9810	6.6454 [0.010]	0.9788	2.5817 [0.108]	0.9800	4.5883 [0.032]	0.9805	5.5652 [0.018]	0.9741	0.1171 [0.732]	0.9795	3.7121 [0.054]
0.9900	0.9938	7.0391 [0.008]	0.9886	0.6875 [0.406]	0.9913	0.8267 [0.363]	0.9891	0.2749 [0.600]	0.9857	6.6237 [0.010]	0.9884	0.9603 [0.327]
0.9950	0.9968	3.0366 [0.081]	0.9926	4.0435 [0.044]	0.9948	0.0229 [0.879]	0.9918	6.6896 [0.009]	0.9901	14.928 [0.000]	0.9936	1.4683 [0.225]
0.9975	0.9980	0.4958 [0.481]	0.9938	15.403 [0.000]	0.9975	0.0024 [0.960]	0.9950	7.4397 [0.006]	0.9938	15.403 [0.000]	0.9948	8.8491 [0.000]
FIAPARCH model – Student-t distribution												
0.9500	0.9586	6.7856 [0.009]	0.9584	6.3937 [0.011]	0.9561	3.4142 [0.064]	0.9584	6.3937 [0.011]	0.9515	0.1978 [0.656]	0.9579	5.6469 [0.017]
0.9750	0.9840	15.453 [0.000]	0.9812	7.2250 [0.007]	0.9808	6.0922 [0.013]	0.9822	9.8153 [0.002]	0.9776	1.1695 [0.279]	0.9808	6.0922 [0.013]
0.9900	0.9960	19.589 [0.000]	0.9940	8.0589 [0.005]	0.9926	3.0895 [0.078]	0.9918	1.5465 [0.213]	0.9899	0.0033 [0.953]	0.9931	4.4507 [0.034]
0.9950	0.9987	16.669 [0.000]	0.9982	11.758 [0.001]	0.9965	2.2154 [0.136]	0.9965	2.2154 [0.136]	0.9950	0.0049 [0.944]	0.9960	0.9934 [0.318]
0.9975	1.0000	NaN	0.9992	7.0100 [0.008]	0.9985	2.0018 [0.157]	0.9982	1.1052 [0.293]	0.9975	0.0024 [0.960]	0.9987	3.2338 [0.072]
FIAPARCH model – skewed Student-t distribution												
0.9500	0.9475	0.4952 [0.481]	0.9534	1.0611 [0.302]	0.9497	0.0037 [0.951]	0.9547	1.9596 [0.161]	0.9515	0.1978 [0.656]	0.9500	0.0001 [0.991]
0.9750	0.9749	0.0018 [0.965]	0.9781	1.6652 [0.196]	0.9766	0.4460 [0.504]	0.9785	2.2528 [0.133]	0.9771	0.7637 [0.382]	0.9753	0.0251 [0.873]
0.9900	0.9923	2.5108 [0.113]	0.9913	0.8267 [0.363]	0.9916	1.1570 [0.282]	0.9911	0.5542 [0.456]	0.9899	0.0033 [0.953]	0.9891	0.2749 [0.600]
0.9950	0.9970	4.0122 [0.045]	0.9953	0.0874 [0.767]	0.9960	0.9939 [0.318]	0.9953	0.0874 [0.767]	0.9950	0.0049 [0.944]	0.9945	0.1367 [0.711]
0.9975	0.9985	2.0018 [0.157]	0.9982	1.1052 [0.293]	0.9987	3.2338 [0.072]	0.9980	0.4958 [0.481]	0.9975	0.0024 [0.960]	0.9972	0.0681 [0.793]

Notes: This table reports the failure rates and the Kupiec LRT statistics for the in-sample VaR. NaN represents the statistics which are not available. The numbers in brackets represent the p-values.

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Table 9

The U.S. and BRICS in-sample VaR analysis (long trading positions case)

	U.S		Brazil		Russia		India		China		South Africa	
Quantile	Failure rate	Kupiec LRT	Failure rate	Kupiec LRT	Failure rate	Kupiec LRT	Failure rate	Kupiec LRT	Failure rate	Kupiec LRT	Failure rate	Kupiec LRT
FIAPARCH model-normal distribution												
0.0500	0.0541	1.4342 [0.231]	0.0489	0.0898 [0.764]	0.0519	0.3154 [0.574]	0.0497	0.0068 [0.933]	0.0499	0.0001 [0.991]	0.0558	2.8441 [0.091]
0.0250	0.0337	11.444 [0.001]	0.0317	7.0062 [0.008]	0.0292	2.9084 [0.088]	0.0275	1.0626 [0.302]	0.0300	3.9621 [0.046]	0.0302	4.3473 [0.037]
0.0100	0.0169	16.545 [0.000]	0.0204	34.287 [0.000]	0.0177	19.896 [0.000]	0.0155	10.652 [0.000]	0.0142	6.6237 [0.010]	0.0174	18.750 [0.000]
0.0050	0.0115	25.653 [0.000]	0.0142	46.676 [0.000]	0.0108	20.778 [0.000]	0.0098	14.928 [0.000]	0.0095	13.588 [0.000]	0.0115	25.653 [0.000]
0.0025	0.0088	39.582 [0.000]	0.0088	39.582 [0.000]	0.0091	42.153 [0.000]	0.0068	21.177 [0.000]	0.0054	10.354 [0.000]	0.0073	25.391 [0.000]
FIAPARCH model -Student-t distribution												
0.0500	0.0622	11.986 [0.001]	0.0546	1.7896 [0.180]	0.0536	1.1172 [0.290]	0.0568	3.8560 [0.049]	0.0553	2.3940 [0.121]	0.0605	8.9398 [0.003]
0.0250	0.0354	16.123 [0.000]	0.0287	2.2922 [0.130]	0.0305	4.7492 [0.029]	0.0253	0.0204 [0.886]	0.0270	0.6981 [0.403]	0.0297	3.5937 [0.058]
0.0100	0.0113	0.6875 [0.406]	0.0140	5.9208 [0.014]	0.0145	7.3616 [0.006]	0.0098	0.0099 [0.920]	0.0103	0.0461 [0.829]	0.0132	4.0280 [0.044]
0.0050	0.0063	1.4683 [0.225]	0.0081	6.6896 [0.009]	0.0049	0.0049 [0.944]	0.0056	0.3419 [0.558]	0.0036	1.5377 [0.214]	0.0066	2.0028 [0.157]
0.0025	0.0036	2.0159 [0.155]	0.0029	0.3165 [0.573]	0.0022	0.1375 [0.710]	0.0039	2.8635 [0.090]	0.0014	2.0018 [0.157]	0.0036	2.0159 [0.155]
FIAPARCH model – skewed Student-t distribution												
0.0500	0.0524	0.4952 [0.482]	0.0509	0.0763 [0.782]	0.0489	0.0898 [0.764]	0.0514	0.1757 [0.675]	0.0548	1.9816 [0.159]	0.0509	0.0763 [0.782]
0.0250	0.0260	0.1949 [0.659]	0.0287	2.2922 [0.130]	0.0258	0.1171 [0.732]	0.0228	0.7637 [0.382]	0.0268	0.5439 [0.460]	0.0248	0.0033 [0.953]
0.0100	0.0103	0.0461 [0.830]	0.0120	1.6342 [0.201]	0.0105	0.1370 [0.711]	0.0093	0.1757 [0.675]	0.0103	0.0461 [0.829]	0.0095	0.0669 [0.795]
0.0050	0.0051	0.0229 [0.879]	0.0046	0.0874 [0.767]	0.0041	0.5757 [0.447]	0.0049	0.0049 [0.944]	0.0036	1.5377 [0.214]	0.0044	0.2757 [0.599]
0.0025	0.0027	0.0681 [0.793]	0.0019	0.4958 [0.481]	0.0024	0.0024 [0.960]	0.0024	0.0024 [0.960]	0.0014	2.0018 [0.157]	0.0034	1.3023 [0.253]

Notes: see notes of Table 9. The numbers in brackets represent the p-values.

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Table 10
The U.S. and BRICS out-of-sample VaR analysis (short trading positions case)

	U.S		Brazil		Russia		India		China		South Africa	
Quantile	Failure rate	Kupiec LRT	Failure rate	Kupiec LRT	Failure rate	Kupiec LRT	Failure rate	Kupiec LRT	Failure rate	Kupiec LRT	Failure rate	Kupiec LRT
FIAPARCH model – normal distribution												
0.9500	0.9650	6.7128 [0.009]	0.9873	51.964 [0.000]	0.9666	8.3072 [0.004]	0.9642	5.9868 [0.014]	0.9730	16.756 [0.000]	0.9698	12.097 [0.001]
0.9750	0.9833	4.0600 [0.043]	0.9920	20.426 [0.000]	0.9849	5.9159 [0.015]	0.9825	3.2797 [0.070]	0.9865	8.2002 [0.004]	0.9849	5.9159 [0.015]
0.9900	0.9936	1.9489 [0.162]	0.9968	8.0799 [0.004]	0.9904	0.0293 [0.864]	0.9912	0.2144 [0.643]	0.9928	1.1539 [0.282]	0.9912	0.2144 [0.643]
0.9950	0.9968	0.9701 [0.324]	0.9976	2.1571 [0.142]	0.9944	0.0754 [0.783]	0.9928	1.0260 [0.311]	0.9952	0.0145 [0.903]	0.9944	0.0754 [0.783]
0.9975	0.9992	2.0089 [0.156]	0.9984	0.4840 [0.487]	0.9952	2.0388 [0.153]	0.9968	0.2117 [0.645]	0.9984	0.4840 [0.486]	0.9960	0.9230 [0.336]
FIAPARCH model – Student-t distribution												
0.9500	0.9611	3.5343 [0.060]	0.9698	12.097 [0.000]	0.9650	6.7128 [0.009]	0.9611	3.5343 [0.060]	0.9690	11.071 [0.001]	0.9706	13.177 [0.000]
0.9750	0.9833	4.0600 [0.043]	0.9865	8.2002 [0.004]	0.9857	7.0016 [0.008]	0.9841	4.9371 [0.026]	0.9873	9.5180 [0.002]	0.9865	8.2002 [0.004]
0.9900	0.9960	6.0036 [0.014]	0.9960	6.0036 [0.014]	0.9944	2.9961 [0.083]	0.9920	0.5831 [0.445]	0.9944	2.9961 [0.083]	0.9944	2.9961 [0.083]
0.9950	0.9992	6.9413 [0.008]	0.9992	6.9413 [0.008]	0.9960	0.2902 [0.590]	0.9976	2.1571 [0.141]	0.9984	4.0251 [0.044]	0.9960	0.2902 [0.590]
0.9975	1.0000	.NaN [0.000]	0.9992	2.0089 [0.156]	0.9984	0.4840 [0.486]	0.9984	0.4840 [0.486]	0.9992	2.0089 [0.156]	1.0000	.NaN [0.000]
FIAPARCH model – skewed Student-t distribution												
0.9500	0.9555	0.8491 [0.356]	0.9674	9.1778 [0.002]	0.9555	0.8491 [0.356]	0.9579	1.7620 [0.184]	0.9698	12.097 [0.001]	0.9658	7.4859 [0.006]
0.9750	0.9777	0.4141 [0.519]	0.9825	3.2797 [0.070]	0.9841	4.9371 [0.026]	0.9801	1.4787 [0.223]	0.9873	9.5180 [0.002]	0.9833	4.0600 [0.043]
0.9900	0.9936	1.9489 [0.162]	0.9944	2.9961 [0.083]	0.9936	1.9489 [0.162]	0.9920	0.5831 [0.445]	0.9952	4.3316 [0.037]	0.9928	1.1539 [0.282]
0.9950	0.9984	4.0251 [0.044]	0.9968	0.9701 [0.324]	0.9944	0.0754 [0.783]	0.9976	2.1571 [0.141]	0.9984	4.0251 [0.045]	0.9960	0.2902 [0.590]
0.9975	0.9992	2.0089 [0.156]	0.9992	2.0089 [0.156]	0.9984	0.4840 [0.486]	0.9984	0.4840 [0.486]	0.9992	2.0089 [0.156]	0.9968	0.2117 [0.645]

Notes: see notes of Table 9. The numbers in brackets represent the p-values.

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Table 11
The U.S. and BRICS out-of-sample VaR analysis (long trading positions case)

	U.S		Brazil		Russia		India		China		South Africa	
Quantile	Failure rate	Kupiec LRT	Failure rate	Kupiec LRT	Failure rate	Kupiec LRT	Failure rate	Kupiec LRT	Failure rate	Kupiec LRT	Failure rate	Kupiec LRT
FIAPARCH model-normal distribution												
0.0500	0.0531	0.2621 [0.608]	0.0158	41.630 [0.000]	0.0444	0.8491 [0.356]	0.0500	0.0000 [1.000]	0.0412	2.1441 [0.143]	0.0531	0.2621 [0.608]
0.0250	0.0380	7.6591 [0.005]	0.0103	14.266 [0.000]	0.0253	0.0080 [0.928]	0.0285	0.6307 [0.427]	0.0222	0.4141 [0.519]	0.0285	0.6307 [0.427]
0.0100	0.0182	6.9696 [0.008]	0.0047	4.3316 [0.037]	0.0142	2.0637 [0.150]	0.0126	0.8538 [0.355]	0.0103	0.0126 [0.910]	0.0126	0.8538 [0.355]
0.0050	0.0103	5.4703 [0.019]	0.0015	4.0251 [0.044]	0.0087	2.8792 [0.089]	0.0071	1.0260 [0.311]	0.0047	0.0145 [0.903]	0.0087	2.8792 [0.089]
0.0025	0.0071	7.2241 [0.007]	0.0015	0.4840 [0.487]	0.0047	2.0388 [0.153]	0.0055	3.4909 [0.061]	0.0023	0.0072 [0.932]	0.0039	0.9230 [0.337]
FIAPARCH model -Student-t distribution												
0.0500	0.0571	1.2964 [0.254]	0.0436	1.1152 [0.290]	0.0507	0.0166 [0.897]	0.0555	0.7914 [0.373]	0.0460	0.4286 [0.512]	0.0605	8.9398 [0.003]
0.0250	0.0373	6.8114 [0.009]	0.0246	0.0081 [0.927]	0.0238	0.0744 [0.785]	0.0301	1.2919 [0.255]	0.0190	1.9929 [0.158]	0.0297	3.5937 [0.058]
0.0100	0.0119	0.4352 [0.509]	0.0063	1.9489 [0.162]	0.0095	0.0293 [0.864]	0.0087	0.2144 [0.643]	0.0055	2.9961 [0.083]	0.0132	4.0280 [0.044]
0.0050	0.0055	0.0754 [0.783]	0.0031	0.9701 [0.324]	0.0031	0.9701 [0.324]	0.0031	0.9701 [0.324]	0.0000	NaN [0.000]	0.0066	2.0028 [0.157]
0.0025	0.0023	0.0072 [0.932]	0.0015	0.4840 [0.486]	0.0007	2.0089 [0.156]	0.0031	0.2117 [0.645]	0.0000	NaN [0.000]	0.0036	2.0159 [0.155]
FIAPARCH model – skewed Student-t distribution												
0.0500	0.0539	0.4076 [0.523]	0.0380	4.0816 [0.043]	0.0484	0.0675 [0.794]	0.0531	0.2621 [0.608]	0.0460	0.4286 [0.512]	0.0507	0.0166 [0.897]
0.0250	0.0317	2.1703 [0.140]	0.0206	1.0463 [0.306]	0.0222	0.4141 [0.519]	0.0230	0.2089 [0.647]	0.0190	1.9929 [0.158]	0.0230	0.2089 [0.647]
0.0100	0.0103	0.0126 [0.910]	0.0039	6.0036 [0.014]	0.0079	0.5831 [0.445]	0.0071	1.1539 [0.282]	0.0055	2.9961 [0.083]	0.0071	1.1539 [0.282]
0.0050	0.0047	0.0145 [0.903]	0.0015	4.0251 [0.044]	0.0015	4.0251 [0.045]	0.0031	0.9701 [0.324]	0.0000	NaN [0.000]	0.0023	2.1571 [0.141]
0.0025	0.0015	0.4840 [0.486]	0.0007	2.0089 [0.156]	0.0007	2.0089 [0.156]	0.0015	0.4840 [0.486]	0.0000	NaN [0.000]	0.0007	2.0089 [0.156]

Notes: see notes of Table 9. NaN denotes the statistics which are not available. The numbers in brackets represent the p-values.

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6. Conclusions

This paper investigates the properties of the conditional volatilities and the time-varying correlations between the United States and the pool of the five most important emerging stock markets, namely the BRICS. To this end, we employ the bivariate DCC-FIAPARCH model to the daily spot index for the period spanning September 1997 to October 2013. To consider the impacts of the GFC and other major events on the linkages between the U.S. and the five BRICS stock markets, we use the adjusted version of Inclán and Tiao (1994) test, developed by Sanso et al. (2004), to identify dates for the GFC and other events. Moreover, to determine the implications of the results on portfolio managers and investors, we complete this study by conducting a portfolio’s VaR analysis based on the FIAPARCH model under three distributions which are the normal, Student-t and skewed Student-t distributions.

Our analysis highlights the presence of leverage effects and fractional integration in conditional volatility for all markets, emphasizing the importance of using the FIAPARCH model. Moreover, the DCC-FIAPARCH model shows significant time-varying correlations between the U.S. and BRICS stock markets. Additionally, using the adjusted Inclán and Tiao (1994) ICSS algorithm, we find several structural changes in the unconditional volatility of the U.S. and the individual BRICS stock markets, with a common break date (i.e., September 15, 2008) which corresponds to the collapse of the Lehman Brothers. This date is chosen as the break point in order to divide the full sample period in two subsamples and define the GFC period.

The estimation results under the two sub-periods support the hypothesis of strengthening re-coupling between the U.S. and each of Brazil, India, China and South Africa after the Lehman Brothers collapse. This is a sign of rising contagion for these countries after this global crisis. In contrast, we support the hypothesis of decoupling between the U.S. and

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Russian stock markets during the GFC. The Russian market has been hit hard since the global crisis and also suffered from currency and political predicaments. Finally, among the three distributed innovations (i.e., normal, Student-t and skewed Student-t distributions), the skewed Student-t FIAPARCH model is suitable to assess the in-sample and out-of-sample VaR performance analysis in almost all cases.

These results have several important implications for policy makers and portfolio investors dealing with the U.S. and BRICS stock markets in forecasting portfolio market risk exposures and determining the existence of diversification benefits in the considered markets. From the asset allocation perspective, the investors with risk aversion can for example invest more funds in Russian stock markets to reduce their portfolio risks during stress periods. Moreover, investors in the BRICS and US countries except Russia can transfer their funds to safe havens (e.g., gold and bond markets) in order to hedge their investments against extreme stock markets exposure (Baur and McDermott, 2010; Baur and Lucey, 2010). In order to avoid greater risks, the investors may adopt an international diversification strategy by including the Islamic financial assets in their portfolios and building optimal portfolio designs accordingly. From the policy makers' perspective, the findings help to build decoupling strategies (i.e., Russian case) to protect against contagion risks.

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Highlights

- We examine the spillover effect between the U.S. and the BRICS (Brazil, Russia, India, China and South Africa) stock markets
- We estimate our DCC-FIAPARCH model which explicitly accommodates long-range memory shifts, leverage effects and asymmetry in the volatility processes.
- We consider the portfolio's VaR forecasting for both short and long positions.

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