# Dynamic global linkages of the BRICS stock markets with the U.S. and Europe under external crisis shocks: Implications for portfolio risk forecasting

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# Dynamic global linkages of the BRICS stock markets with the U.S. and Europe under external crisis shocks: Implications for portfolio risk forecasting

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**Abstract**
Crisis shocks often lead to changes in the interdependence across stock markets, and thus risk assessment and management. This paper investigates the extent to which the global financial crisis of 2008-2009, which was triggered by the US subprime crisis in 2007, and the European debt crisis started at the end of 2009, affect the interdependence of the leading emerging markets of the BRICS countries with those of the United States and Europe. Our empirical analysis makes use of the FIAPARCH model combined with the Dynamic Equicorrelation (DECO-FIAPARCH), which allows for the estimation of market linkage for a large group of countries as a whole, while controlling for asymmetric volatility and long memory. The results reveal the presence of important changes in the time-varying linkages of the BRICS stock markets with the US and European ones. In particular, the average linkages have significantly been higher between 2007 and the first half of 2012 than the remaining part of the sample, and there is also evidence of structural change around the Lehman Brothers collapse. We also show the effects of these stylized facts on portfolio risk assessment and forecasting.

*JEL classification*: G14; G15.
*Keywords:* dynamic linkages; crisis shocks; risk assessment; DECO-FIAPARCH.

## 1. Introduction

Understanding the characteristics of financial market returns, volatility and interdependence provides important information for investors interested in portfolio diversification and risk management, particularly during times of financial distress and crises. Past studies have extensively examined changes in financial market behaviors such as sudden changes which also have important implications for the analysis of crisis transmission and systematic risk (see, among others, Forbes and Rigobon, 2002; Bekaert et al., 2005; Bekaert et al., 2014; Pragidis et al., 2015; Dungey et al., 2015). A common result from this strand of the literature shows that the transmission of shocks as measured by return correlations and dependency as well as by volatility spillovers from one market to another increases in times of crises, providing evidence of contagious effects across financial markets. In particular, Bekaert et al. (2014) use an international three-factor asset-pricing model to analyze the transmission of crises to country-industry portfolios.[1] The authors define contagion by the presence of unexplained increases in factor loadings, and also find evidence of systematic contagion from the US market and the global financial factor, although the effects are not large.

In this paper, we attempt to measure and detect variations in the dynamic linkages of the BRICS stock markets (Brazil, Russia, India, China and South Africa) with those of the United States and the European region, with emphasis on the global financial crisis (GFC) of 2008-2009 and the European public debt crisis that dates back to the end of 2009. Our special focus on the BRICS stock markets is motivated by the important role these countries plays in the world financial landscape and the potential diversification benefits they can offer to global investors, promoted by their high potential economic growth. It is also inspired by the future economic aptitudes that can afford from building new institutions such as the benefits from the establishment of their common "New Development Bank" to foster economic cooperation

[1] The factors considered include the US market factor, global financial factor, and domestic market factor.

and to finance infrastructure and sustainable projects. Those who have dealt with the future of BRICS show that, for examples, China's GDP which was around US$8.4 trillion in 2012 is expected to rise to about US$16.15 trillion in 2020.[2] Over the same period, the total GDP for the four BRIC countries without South Africa is expected to grow by 57.53%, rising from US$14.276 trillion to US$22.49 trillion. In addition, global investors can design dedicated investment strategies for the BRICS markets, given those markets' common characteristics in terms of high average returns, high idiosyncratic volatility, improved market efficiency, increased liquidity, enhanced capital mobility, and greater dynamic linkages with developed markets. Several past studies note that these favorable features have largely been the result of the vast stock market liberalization reforms which have been implemented by almost all emerging markets include those of the BRICS since the early 1980s (e.g., DeSantis and Imrohoroglu, 1997; Bekaert et al., 2000; Kim and Singal, 2000).

Another reason that motivates our investigation of the BRICS market linkages with markets in the United States and the European region is the occurrence of the recent crises (the GFC and the European debt crisis in particular), which may have changed the behavior of return and volatility in these markets, and in turn portfolio diversification benefits and risk management. In terms of trade, China is the second largest trading partner with the European region after the United States, accounting for 14% of total trade in goods compared to 15% for the United States in 2014. With respect to the United States, China stands as the third-largest export market for US goods during the same year. In fact, the United States' trade in goods with China is almost nine times its trade with India. Russia also accounts for 8% of total trade with the European countries. In 2013 Brazil was the 7$^{th}$ largest goods export market for the United States. However, the trade ties between the U.S. and Russia are weak. The U.S. goods exports to Russia represents to less than 0.1% of the U.S. GDP, while the U.S. goods

[2] http://www.statista.com/topics/1393/bric-countries/.

imports from Russia is below 0.2% of the U.S. GDP. When it comes to India, this country is a major trading partner with Germany within the European Union, and has strong trade links with the United States (exports) and China (imports). Evidence of increased interdependence should be indicative of lower diversification gains but greater potential contagious effects if the external shocks are severe. Aside from the trade and market linkages, we show how our results affect risk assessment and forecasting of the stock portfolios involving the BRICS stock markets based on the Value at Risk (VaR) framework.

The recent literature has examined some critical issues related to the BRICS stock markets at times of crisis, such as the return and volatility behavior, market comovement, volatility spillovers, and contagion risk (e.g., Bhar and Nikolova, 2009; Xu et al., Chiang et al., 2013; Bianconi et al., 2013; Dimitriou et al., 2013; Cho et al., 2015).[3] Using various econometric methods, these studies mainly show that: i) the BRICS markets significantly react to the shocks caused by the recent GFC and the Eurozone public debt crisis; ii) there is evidence to suggest a shift into a regime of increased comovement with the transmission of contagious effects to the BRICS markets; and iii) the recent GFC has significant impacts on the behavior of emerging markets. For example, the findings of Aloui et al. (2011) based on a copula-GARCH approach confirm not only the existence of a time-varying dependency between the BRIC and the US stock markets, but also the high persistence of this dependence. Ahmad et al. (2013) focus on stock markets of Brazil, Russia, India, Indonesia, China, South Korea and South Africa (BRIICKS) and base their contagion analysis on a multivariate DCC-GARCH model. They show that Ireland, Italy and Spain transmitted the most contagious effects to the BRIICKS markets during the Eurozone debt crisis, of which the four BRIC stock markets are

[3] See Wang et al. (2003), Bhar and Nikolova (2009), Beirne et al. (2010), and Abbas et al. (2013) for detailed discussions of the literature on the volatility and return spillover between emerging and developed markets. For example, Beirne et al. (2010) use trivariate VAR-GARCH models to investigate the volatility transmission from the regional and global markets to 41 emerging markets in Asia, Europe, Latin America, and the Middle East and North Africa, and find evidence of spillover effects for most sample markets. They also document the time-varying nature of cross-market linkages. Some evidence of the US financial and real news effects on the CDS spreads of emerging market sovereign bonds can be found in Dooley and Hutchison (2009).

the most affected. For their part, by using a DCC-EGARCH model, Hwang et al. (2013) find that the recent GFC has led to different patterns of market comovements among the US and emerging stock markets including the BRICS, and also changed their conditional correlations. The latter result is also found in Zhang et al. (2013). Using the DCC-FIAPARCH model, Dimitriou et al. (2013) also document a change in market linkage between the BRICs and the US stock markets following the Lehman Brothers collapse, which can be viewed as a shift in investors' risk appetite. They also uncover a larger dependence in bullish market periods than tin bearish ones.

This paper extends the literature on spillover effects to the emerging stock markets by using the bivariate DECO-FIAPARCH model under switching of different regimes. First, it examines the dynamic linkages of the BRICS stock markets with the U.S. and European markets. Second, to the extent that regime switching and its associated spillover effects may directly affect return and volatility structures, we investigate how different market regimes such as stable regimes and crisis regimes defined by the GFC of 2008-2009 impacts the spillovers among the BRICS and the major markets of the U.S. and European Union. It is worth noting that we take the GFC effects into account by first detecting the existence of potential different regimes with the use of regime switching in order to differentiate between the impacts of the tranquil or stable periods and those of the volatile/crisis periods. Third, we use the Dynamic Conditional Equicorrelation Fractionally Integrated Asymmetric Power ARCH (DECO-FIAPARCH) model to determine the spillover effects between the BRICS and each of the U.S. and European stock markets. This empirical approach accommodates several very important stylized facts of stock returns such as the persistence level, the long memory and the asymmetry properties of the conditional variance processes during stable and volatile periods. We assess the changes in those properties as a result of the onset of the GFC which has important implications for market contagion analysis and VaR forecast accuracy of a portfolio. More importantly, the DECO modeling in Engle and Kelly (2012) provides an efficient way to assess in depth the variability in correlations during the different market regimes. The DECO model is a special case of the DCC model in which the correlations across all pairs of markets are equal, but the common equicorrelation is time-varying. Despite this seemingly strong restriction, the DECO model provides consistent estimates of DCC parameters in large systems and, in this study, it allows us to quantify the linkages of the BRICS, the United States and Europe as a common group, for the purpose of portfolio diversification to assets issued by these markets. Finally, we analyze the result implications for portfolio decision-making and risk forecasting. More precisely, we show how these results help improve the portfolios' VaR forecasting for both short and long positions.

Our empirical results mainly confirm the existence of a regime shift and show strong evidence of dynamic linkages and heightened recoupling of the BRICS stock markets with those of the U.S. and Europe, following the occurrence of the GFC. Moreover, among the different testing specifications, the skewed Student-t DECO-FIAPARCH model is found to be the most suitable for improving the VaR forecasting efficiency.

The remainder of this paper is structured as follows. Section 2 presents the data used and the empirical method. Section 3 reports and discusses the empirical results. Section 4 concludes the paper.

## 2. Data and methodology

### *2.1 Data*

Our study uses daily MSCI stock market indices (denominated in US dollars) of the BRICS stock markets. For their part, stock markets in the United States and the European region are represented by the S&P 500 index and the STOXX 600 index, respectively. These two developed markets have been the "epicenter" of the 2008-2009 GFC and the Eurozone debt crisis. The sample period ranges from 29 September 1997 to 10 September 2015. All the data are sourced from Datastream International database. Figure 1 shows the stock price dynamics of the U.S., European and BRICS markets. We particularly observe a significant drop in all stock market indices in response to Lehman Brothers collapse in September 2008.

Table 1 shows the descriptive statistics of the daily log returns for the BRICS, the U.S. and the European stock markets. The returns are on average positive for all markets, except for China. The Indian stock market achieved the highest return, followed by the U.S. and South African stock markets. On the other hand, the unconditional volatility (the standard deviation) ranges from 1.25% (South Africa) to 3.2% (Russia). The return series are also found to be asymmetric, fat-tailed and high-peaked, in views of the skewness and kurtosis values. This departure from normality is confirmed by the Jarque-Bera test. Moreover, the results from the Engle (1992) test for conditional heterogeneity and the Ljung-Box test applied to residuals and squared residuals, respectively, show evidence of ARCH effects and serial correlations, which supports the use of GARCH approach for volatility modeling and VaR forecasting. Finally, the hypothesis of stationarity cannot be rejected for return series, as indicated by the commonly-used unit root and stationarity tests (ADF, PP and KPSS).

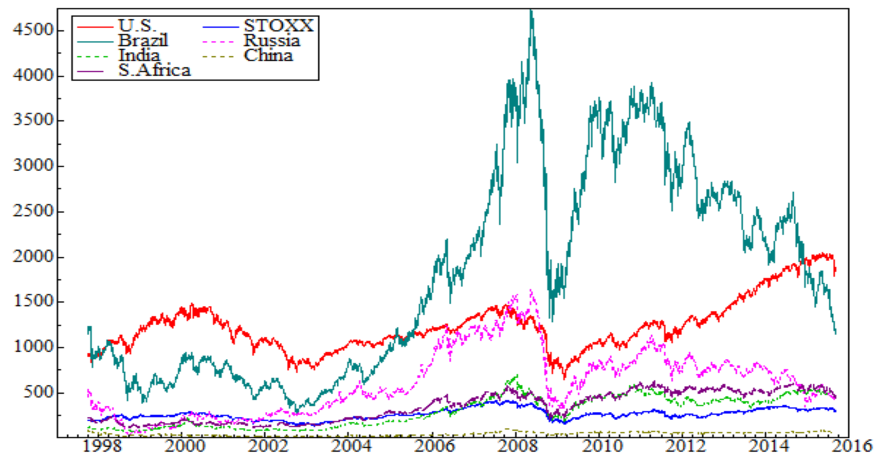


**Fig. 1.** Time-paths of the daily indices for the U.S., Europe and the five BRICS stock markets

**Table 1**: Stochastic properties of daily returns of the U.S., Europe and BRICS stock markets

| | U.S. | Europe | Brazil | Russia | India | China | South Africa |
|---|---|---|---|---|---|---|---|
| Mean | 0.0002 | 0.0001 | 0.0001 | 0.0001 | 0.0003 | -0.0001 | 0.0002 |
| Max. | 0.1104 | 0.1062 | 0.1733 | 0.2422 | 0.1948 | 0.1404 | 0.1235 |
| Min. | -0.0950 | -0.1018 | -0.1832 | -0.2809 | -0.1209 | -0.1444 | -0.1357 |
| Std. dev. | 0.0126 | 0.0139 | 0.0242 | 0.0320 | 0.0178 | 0.0199 | 0.0125 |
| Skewness | -0.2334 | -0.1058 | -0.2369 | -0.4214 | -0.1114 | 0.0309 | -0.3951 |
| Kurtosis | 10.668 | 9.0822 | 10.366 | 14.917 | 9.9630 | 8.1180 | 7.7240 |
| Jarque-Bera | 11202*** | 7029*** | 10339*** | 27087*** | 9214*** | 4972*** | 3838*** |
| Q(20) | 84.00*** | 80.36*** | 81.32*** | 73.31*** | 87.96*** | 85.24*** | 81.82*** |
| $Q^2(20)$ | 5564*** | 4629 *** | 3221*** | 3607*** | 1036*** | 2792*** | 2980*** |
| ADF | -51.53*** | -41.94*** | -63.06*** | -62.94*** | -62.89*** | -61.36*** | -63.84*** |
| PP | -73.09*** | -67.31*** | -62.93*** | -62.95*** | -63.22*** | -61.19*** | -63.74*** |
| KPSS | 0.097 | 0.049 | 0.219 | 0.122 | 0.081 | 0.323 | 0.0899 |
| ARCH-LM (10) | 140.44*** | 123.97*** | 121.72*** | 73.76*** | 37.52*** | 81.07*** | 81.82*** |

Notes: Europe is represented by the STOXX 600 index. 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. The ARCH-LM(10) test of Engle (1982) is to check the presence of the 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.

### *2.2 The DECO-FIAPARCH model*

Engle (2002) develops the DCC-GARCH which offers the flexibility to simultaneously model the multivariate conditional volatility of stock returns and their time-varying correlations. Engle and Kelly (2012) propose the Dynamic Equicorrelation GARCH model (DECO-GARCH) in which the average of the conditional correlations is set to equal to the average of all pair correlations. Accordingly, we are able to measure the time-variations in the linkages of all markets under consideration over the study period. By construction, the DECO-GARCH model is thus a special case of the Constant Conditional Correlation GARCH (CCC-GARCH) and the DCC-GARCH, and has advantages over the latter, particularly when we deal with large-scale correlation matrices. Engle and Kelly (2012) use the same structure to construct the covariance matrix as in the DCC-GARCH model. To the extent that our paper attempts to quantify the linkages of the BRICS markets with two global markets (the United States and Europe), the DECO-GARCH model suits our research question best.

Consider a vector of $n$ return series $r_t = [r_{1,t}, \dots, r_{n,t}]$. We first estimate the following mean equation:

$$r_t = \mu + \varphi r_{t-1} + \varepsilon_t \tag{1}$$

where μ is a vector of constant terms, $\varphi$ is the coefficient vector corresponding to autoregressive terms and $\varepsilon_t = [\varepsilon_{1,t}, \ldots \varepsilon_{n,t}]'$ is the vector of residuals.

Next, we use the FIAPARCH (1,$d$,1) model developed by Tse (1998) to estimate the conditional volatilities $h_{i,t}^{\delta/2}$ as specified in (Eq. (2)) below, because this estimation allows us to capture not only the volatility leverage, but also long memory in the conditional volatility process.

$$h_t^{\delta/2} = \omega\big(1-\beta(L)\big)^{-1} + \Big[1-\big(1-\beta(L)\big)^{-1}\emptyset(L)(1-L)^d\Big](|\varepsilon_t| - \lambda\varepsilon_t)^\delta, \tag{2}$$

where $\omega, \beta,\ \emptyset,$ and $d$ are the parameters to be estimated, and $0 \leq d \leq 1$. Moreover, $L$ and $\delta$ denote the lag operator and the power term of returns for the predictable structure in the volatility persistence, respectively. It is worth noting that negative shocks have greater effects on volatility than positive shocks if $\lambda > 0$, underlying the presence of the leverage effects.

Assume that $E_{t-1}[\varepsilon_t] = 0$ and $E_{t-1}[\varepsilon_t\varepsilon_t'] = H_t$, where $E_t[\cdot]$ is the conditional expectation using the information set available at time $t$. The asset conditional variance-covariance matrix $H_t$ can be written as

$$H_t = D_t^{1/2}\, R_t\, D_t^{1/2}, \tag{3}$$

where $R_t = [\rho_{ij,t}]$ is the conditional correlation matrix, while the diagonal matrix of the conditional variances is given by $D_t = \mathrm{diag}\,(h_{1,t}, \cdots, h_{n,t})$. Engle (2002) models the right-hand side of Eq. (3) rather than $H_t$ directly by proposing the following dynamic correlation structure, called DCC:

$$R_t = \{Q_t^*\}^{-1/2} Q_t (Q_t^*)^{-1/2}, \tag{4}$$

$$Q_t^* = \mathrm{diag}\,[Q_t], \tag{5}$$

$$Q_t = [q_{ij,t}] = (1 - a - b)S + a u_{t-1} u'_{t-1} + b Q_{t-1}, \tag{6}$$

where $u_{i,t}$ are the standardized residuals, i.e., $u_{i,t} = \varepsilon_{i,t}/h_{i,t}$ , $S = [s_{i,j}] = E[u_t u'_t]$ is the $n \times n$ unconditional covariance matrix of $u_t$, and $a$ and $b$ are non-negative scalars satisfying $a \geq 0, b \geq 0, a + b < 1$.

In this context, Aielli (2013) proves that the estimation of the covariance matrix $Q_t$ by this way is inconsistent since $E[R_t] \neq E[Q_t]$ and suggests the following consistent model with the correlation-driving process (cDCC):

$$Q_t = (1 - a - b)S^* + a\left(Q_{t-1}^{*1/2}\, u_{t-1}\, u'_{t-1}\, Q_{t-1}^{*1/2}\right) + b Q_{t-1}, \tag{7}$$

where $S^*$ is the unconditional covariance matrix of $Q_t^{*1/2} u_t$.

Engle and Kelly (2012) suggest to model $\rho_t$ by using the cDCC process to obtain the conditional correlation matrix $Q_t$ and then taking the mean of its off-diagonal elements. This approach, which reduces the estimation time, is called the dynamic equicorrelation (DECO) model. The scalar equicorrelation is defined as

$$\rho_t^{DECO} = \frac{1}{n(n-1)}(J'_n R_t^{cDCC} J_n - n) = \frac{2}{n(n-1)} \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \frac{q_{ij,t}}{\sqrt{q_{ii,t} q_{jj,t}}} \tag{8}$$

where $q_{ij,t} = \rho_t^{DECO} + \alpha_{DECO}\left(u_{i,t-1} u_{j,t-1} - \rho_t^{DECO}\right) + \beta_{DECO}\left(q_{ij,t-1} - \rho_t^{DECO}\right)$, which is the $(i,j)^{th}$ element of the matrix $Q_t$. We then use this scalar equicorrelation to estimate the conditional correlation matrix:

$$R_t = (1 - \rho_t) I_n + \rho_t J_n \tag{9}$$

where $J_n$ is the $n \times n$ matrix of ones and $I_n$ is the $n$-dimensional identity matrix. This assumption of equicorrelation leads to a much simpler likelihood equation when $\rho_t$ is given by Eq. (7):

$$L = -\frac{1}{T}\sum_{t=1}^{T}\left(ln((1-\rho_t)^{n-1}(1+(n-1)\rho_t)\right) + \frac{1}{1-\rho_t}\left(\sum_{i=1}^{n}\varepsilon_{i,t}^2 - \frac{\rho_t}{1+(n-1)\rho_t}\left(\sum_{i=1}^{n}\varepsilon_{i,t}^2\right)\right) \quad (10)$$

In the new structure, the DECO modeling is less burdensome and computationally quicker to estimate, because we avoid the inversion of matrix $R_t$. Besides, it makes it possible to represent the comovement of a group of markets with a single dynamic correlation coefficient.

*2.3 Value-at-Risk (VaR) forecasting*

The Value at Risk (VaR) model has become a popular benchmark for measuring portfolio market risks (e.g., Jorian, 2007; Wu and Shieh, 2007, and Christoffersen, 2009). In this paper, we estimate the DECO-FIAPARCH model and use the empirical results to compute the one-day-ahead VaR under three different return distributions including the Normal, Student-$t$, and skewed Student -$t$ distributed innovations.

Assuming the normal distribution, the one-day-ahead VaRs for a portfolio containing long (buy) and short (sell) trading positions can be specified as

$$VaR_{t,long} = \mu_t + z_\alpha \hat{\sigma}_t \quad (11)$$

$$VaR_{t,short} = \mu_t + z_{1-\alpha} \hat{\sigma}_t \quad (12)$$

where $\mu_t$ and $\hat{\sigma}_t$ denote respectively the conditional mean and variance at time $t$, and $z_\alpha$ is the left quantile at the $\alpha$ % level for the normal distribution, while $z_{1-\alpha}$ is the right quantile at the $\alpha$% confidence level. Similarly, we obtain the VaRs under the Student-t and skew Student-t distributions by using their respective left and right quantiles at the $\alpha$% level instead of those of the normal distribution (i.e., $z_\alpha$ and $z_{1-\alpha}$).[4]

Regarding the out-of-sample VaR forecasting analysis, we follow the procedure proposed by Wu and Shieh (2007) to compute the one-day-ahead VaR for each of the considered portfolios and to evaluate the performance of competing VaR models. Indeed, we re-estimate

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

the empirical models every 100 observations using a rolling regression approach, and retain the last 1250 (5-year) observations of the sample as the out-of-sample period.

We evaluate the accuracy of the VaR forecasting through the calculation of the failure rate for the left and right tails of the return distribution. The failure rate $f$ refers to the ratio of the number of times the positive (negative) returns go beyond (below) the estimated VaR to the sample size. Giot and Laurent (2003) show that the accuracy of an empirical model is then examined by testing the hypothesis $\begin{cases} H_0: f = \alpha \\ \mathrm{H}_1\ f \neq \alpha \end{cases}$. If the VaR model is correctly specified, then the failure rate is close to the pre-determined VaR confidence level ($\alpha$%). The Kupiec (1995) LR test statistic is expressed as follows:

$$LR = -2ln[(1-\alpha)^{N-x}\alpha^{x}] + 2ln\left[\left(1-\hat{f}\right)^{N-x}\hat{f}^{x}\right] \quad (13)$$

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

## 3. Empirical results

This section discusses the estimation results for the full sample period, the inclusion of structural breaks, and the GFC effects on the relationships among the developed (European and U.S.) and the BRICS stock markets, and the VaR analysis.

*3.1 Estimation for the full sample period*

Table 2 presents the estimation results of the DECO-FIAPARCH ($1,d,1$) model with Student-t distributed innovations over the full sample period.[5] With respect to the mean equation, the autoregressive parameter is found to be positive and statistically significant at the 1% level for all cases. This finding suggests that past information is rapidly reflected in the current returns

[5] The lag order ($1,d,1$) is chosen by using the Akaike information criteria (AIC) and the Schwarz information criteria (SIC). The estimation results of the DECO-FIAPARCH($1,d,1$) model with other return distributions (Gaussian and skewed Student-t) are relatively similar and can be made available under request.

of the stock markets under consideration. As to the parameters of the conditional variance equation, the estimated coefficient of the leverage effects ($\lambda$) is positive and significant for the five BRICS markets, which is evidence of asymmetric volatility phenomenon and implies that negative shocks of similar magnitude affecting stock returns have larger impacts on the conditional volatility than positive shocks do. The significance of the fractional integrated coefficient ($d$) for all the markets at conventional levels, which ranges from 0.2926 (South Africa) to 0.5344 (United States), suggests that stock market volatility has a high level of persistence.

**Table 2:** Estimation of the AR(1)-DECO-FIAPARCH(1,$d$,1) model.

| | U.S. | Europe | Brazil | Russia | India | China | S. Africa |
|---|---|---|---|---|---|---|---|
| Panel A: Estimates of the conditional mean and variance equations | | | | | | | |
| Const.(M) | 0.0484$^{***}$ | 0.0584$^{***}$ | -0.0165 | 0.0103 | 0.0600$^{**}$ | 0.0121 | 0.0261 |
| | (0.0126) | (0.0151) | (0.0285) | (0.0309) | (0.0248) | (0.0249) | (0.0243) |
| AR(1) | -0.0435$^{***}$ | -0.0017$^{***}$ | 0.0993$^{***}$ | 0.0662$^{***}$ | 0.0869$^{***}$ | 0.0871$^{***}$ | 0.0546$^{***}$ |
| | (0.0142) | (0.0154) | (0.0162) | (0.0159) | (0.0177) | (0.0153) | (0.0157) |
| Const. (V) | 0.3790 | 0. 2031$^{***}$ | 0.4442 | 0.1793$^{**}$ | 0.4262$^{***}$ | 0.7918$^{***}$ | 0.3001$^{***}$ |
| | (0.2283) | (0.7415) | (0.1306) | (0.0883) | (0.1066) | (0.2669) | (0.0733) |
| d-FIGARCH | 0.5344$^{***}$ | 0.4779$^{***}$ | 0.3080$^{***}$ | 0.4631$^{***}$ | 0.3522$^{***}$ | 0.4517$^{***}$ | 0.2926$^{***}$ |
| | (0.0678) | (0.0443) | (0.0365) | (0.0593) | (0.0468) | (0.0462) | (0.0379) |
| ARCH | 0.0320 | 0.1477$^{***}$ | 0.1080 | 0.1344 | 0.1728$^{***}$ | 0.2407$^{***}$ | 0.2740$^{***}$ |
| | (0.0697) | (0.0493) | (0.0751) | (0.0813) | (0.0480) | (0.0495) | (0.0650) |
| GARCH | 0.5272$^{***}$ | 0.5436$^{***}$ | 0.3477$^{***}$ | 0.4927$^{***}$ | 0.4420$^{***}$ | 0.5958$^{***}$ | 0.4905$^{***}$ |
| | (0.0527) | (0.0622) | (0.0833) | (0.1134) | (0.0531) | (0.0632) | (0.0773) |
| APARCH | 0.9891$^{***}$ | 0.9999$^{***}$ | 0.6810$^{***}$ | 0.3353$^{***}$ | 0.5066$^{***}$ | 0.2864$^{***}$ | 0.7922$^{***}$ |
| ($\lambda$) | (0.0331) | (0.0341) | (0.1614) | (0.0777) | (0.1363) | (0.0634) | (0.1675) |
| APARCH | 1.5927$^{***}$ | 1.2523$^{***}$ | 1.3664$^{***}$ | 1.5139$^{***}$ | 1.4444$^{***}$ | 1.6577$^{***}$ | 1.2799$^{***}$ |
| ($\delta$) | (0.1740) | (0.1520) | (0.1124) | (0.1606) | (0.1410) | (0.1158) | (0.1040) |
| Panel B: Estimates of the DECO process | | | | | | | |
| Average | 0.3489$^{***}$ | | | | | | |
| CORij | (0.0822) | | | | | | |
| $\alpha_{DECO}$ | 0.0117$^{***}$ | | | | | | |
| | (0.0021) | | | | | | |
| $\beta_{DECO}$ | 0.9882$^{***}$ | | | | | | |
| | (0.0026) | | | | | | |
| Panel C: Diagnostic tests | | | | | | | |
| Q(20) | 29.081 | 55.053 | 21.000 | 26.076 | 34.474 | 37.503 | 19.144 |
| | [0.0647] | [0.0000] | [0.3367] | [0.1280] | [0.0161] | [0.0068] | [0.4475] |
| $Q^2(20)$ | 17.964 | 14.401 | 18.179 | 9.3878 | 12.647 | 12.629 | 19.109 |
| | [0.4580] | [0.8095] | [0.4439] | [0.9500] | [0.8120] | [0.8131] | [0.3851] |

Notes: Europe is represented by the STOXX index. 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 standard errors are in parentheses and the p-values are in brackets.

Turning out to the estimates of the DECO process ($\alpha_{DECO}$ and $\beta_{DECO}$), they are positive and highly significant, thus underlying the fact that the cross-market linkages of our markets at the group level vary over time, under the effects of both past return innovations and past correlation persistence. While the average dynamic equicorrelation is positive (0.348), it still remains low. Potential diversification benefits could thus be achieved for portfolios involving the BRICS, the US and the European stock markets. A close look at the diagnostic tests in Table 2 provided by the Ljung-Box test statistics for the standardized and the squared standardized residuals shows that our empirical model is correctly specified, since the null hypothesis of no serial correlation cannot be rejected for most cases.

Fig. 2 displays the dynamic equicorrelation for the group of the BRICS, U.S. and European markets. We observe time-varying correlations over the sample period, meaning that investors should frequently change their portfolio structure. Moreover, the correlation level increases significantly during 2008-2012, which corresponds to the most severe periods of the GFC and the European sovereign debt crisis periods. This result also supports the recoupling hypothesis (contagion effects).

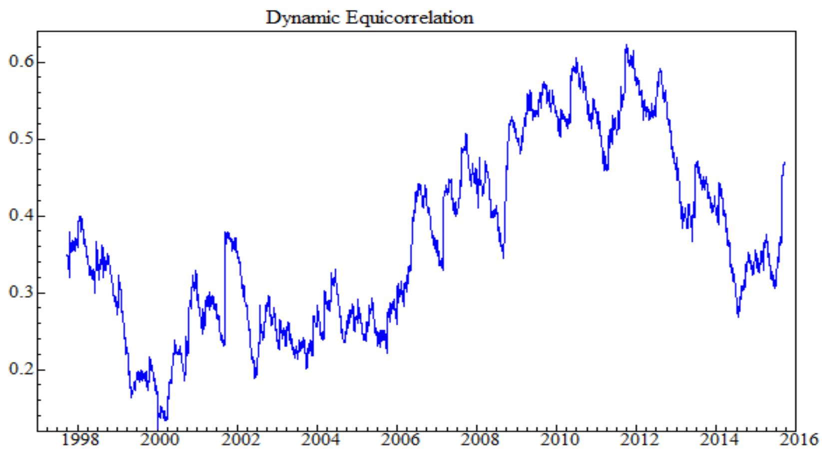


**Fig. 2.** Dynamic equicorrelation

*3.2 Regime switching analysis*

The presence of potential structural breaks may imply that the linkages among sample markets experience different phases of dynamics. For this purpose, we use a Markov-switching dynamic regression (MS-DR) model to identify the potential of regime shifts in the data-generating processes of our return series. The MS-DR model is advantageous in that it allows the data to determine the beginning and end of each phase of the crisis, and distinguish between a regime zero ('stable' regime) and a regime one ('volatile/crisis' regime).[6] Here, regimes zero and one indicate lower and higher values of conditional volatility, respectively.

**Table 3:** Results of the multiple regime test for the US and European stock markets

| Regime change dates | Possible corresponding events |
|---|---|
| 04/28/2003 | Gulf war |
| 07/09/2007 | U.S. subprime crisis |
| 09/15/2008 | Lehman Brothers collapse |
| 12/01/2008 | Global financial crisis of 2008-2009 |
| 05/18/2009 | Sign of economic recovery |
| 03/14/2011 | European debt crisis |

Notes: The structural break tests are conducted by the MS-DR model.

Fig. 3 displays the smoothed regime probabilities of conditional volatility including the volatile regime (the grey shading). We show, in Table 3, the common multiple regime shifts in the unconditional variance for two developed markets, the U.S. and Europe, which seem to coincide with major economic and political events (Gulf war, U.S. subprime crisis of 2007, the global financial crisis of 2007-2009, and the European public debt crisis since the end of 2009).[7] When the regime shifts between the developed and the BRICS markets are compared, we see that they share a common breakpoint on the 15$^{th}$ of September 2008 which corresponded to the bankruptcy of Lehman Brothers and marked a sharp decline in stock prices in sample markets. Next, this break date is chosen to examine the crisis effects on the interactions among the sample markets.

[6] Several structural break tests can be used to examine the sudden changes in financial time series. The Bai and Perron (2003), the CUSUM and the Inclán and Tiao (1994) tests are among the most popular tests. For example, the Bai and Perron (2003) test discloses the exact number of breaks and their corresponding dates of occurrence. This test 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. The Inclán and Tiao (1994) ICSS test is unable to recognize difference between unconditional and conditional volatility. Here, our model is an extension of the Markov-switching autoregressive models (MS-AR) and the Markov switching regression model of the type considered by Hamilton (1989).

[7] Ten regime changes are also found for Brazil, eleven for Russia and thirteen for the remaining markets of the BRICS group. These results can be made entirely available upon request to the corresponding author.

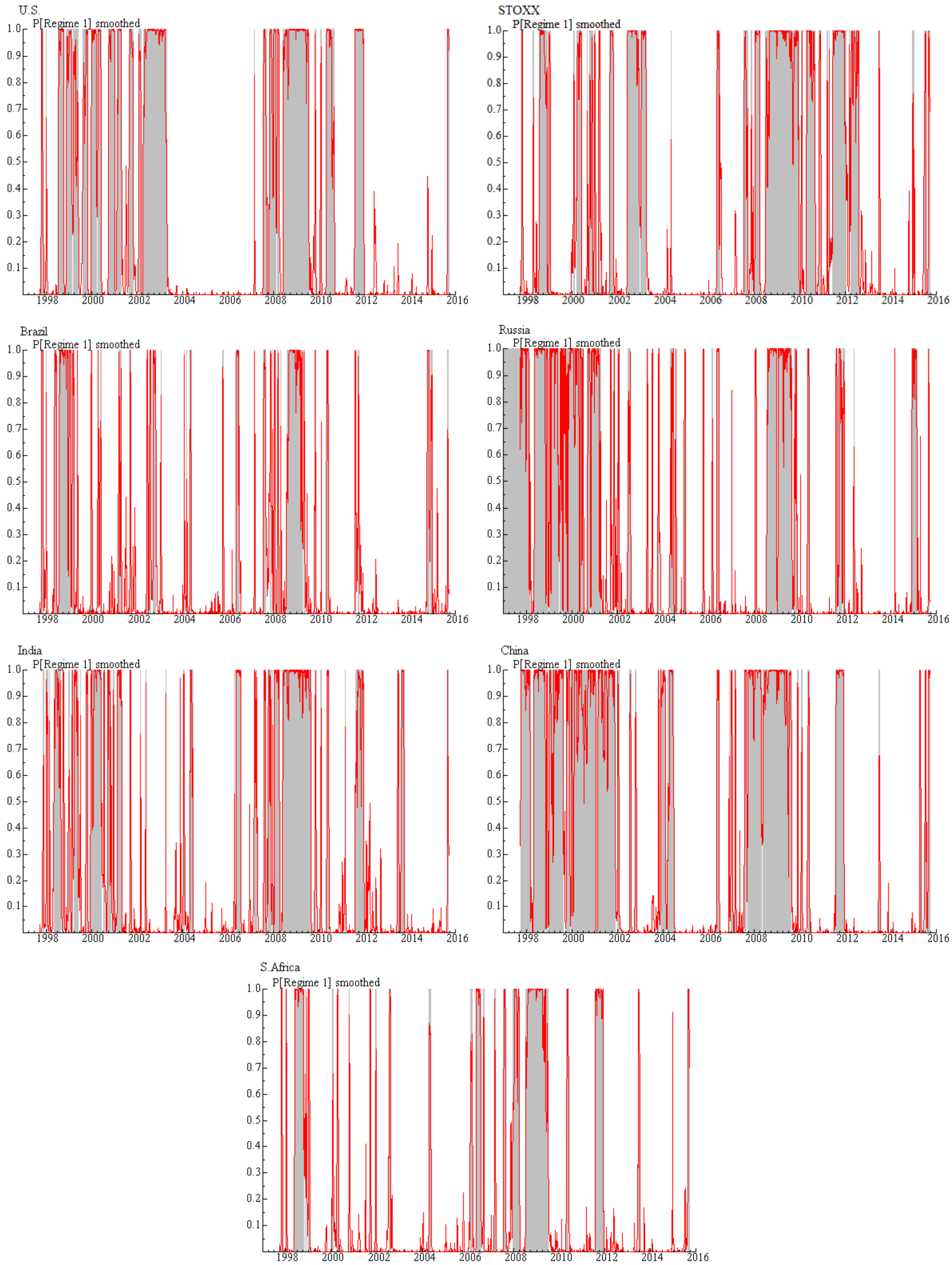


**Fig. 3:** Regimes of the U.S., European and BRICS market conditional volatilities

Notes: The shaded areas highlight regimes of excess volatility according to the Markov switching dynamic regression (MS-DR) model.

*3.3 The interactions among the developed and BRICS markets under regime switching*

The estimation results of the DECO-FIAPARCH $(1,d,1)$ for sample markets before and after the 2008-2009 GFC are reported in Table 4 and Table 5, respectively. An overall comparison indicates that the onset of the GFC has significant effects on the behavior of conditional volatility, which confirms the findings of some related studies such as Dimitriou et al. (2013) and Hwang et al. (2013). More precisely, while both tables commonly show evidence of long memory effects on volatility (i.e., the parameter $d$ is highly significant at the 1% level), the volatility dependence patterns are more apparent after the collapse of Lehman Brothers, with the exception of the Russian and Chinese markets. Therefore, the GFC has made the future volatility more predictable from its past values, which can be explained by the long-lasting reaction of market participants to the crisis shocks.

Another important difference is the increase in the degree of volatility persistence in the crisis period. Indeed, the estimates of the coefficients associated with the GARCH terms are highly significant for all markets in Table 5, but are not significant in the case of Brazil and South Africa before the crisis. We also find a difference in terms of leverage effects ($\lambda$ parameters) which increased for all stock markets following the crisis, except for the case of the European, Brazilian and Indian markets. What is finally interesting to note is the harmful effect of the GFC on asset allocation and benefits from diversifying portfolios internationally. Our results show a significant increase in the correlation between sample markets at the group level since the average equicorrelation almost doubled after the crisis, shifting from 0.3151 (Table 4) to 0.6326 (Table 5). This evidence confirms the rising comovement during periods of crisis found in past studies (Ahmad et al., 2013; Dimitriou et al., 2013) provide a similar result since the BRICS markets are found to be strongly hit by the contagion shock during the Eurozone crisis) and the resulting reduction in the diversification potential for portfolios containing stocks of the sample markets.

**Table 4:** Estimation of the AR(1)-FIAPARCH(1,$d$,1)-DECO model in the pre-crisis period

| | U.S. | Europe | Brazil | Russia | India | China | S. Africa |
|---|---|---|---|---|---|---|---|
| Panel A: Estimates of the conditional mean and variance equations | | | | | | | |
| Const. (M) | -0.0147 | 0.0204 | 0.0415 | 0.0752 | 0.1038*** | 0.0327 | 0.0635 |
| | (0.0192) | (0.0189) | (0.0434) | (0.0446) | (0.0337) | (0.0363) | (0.0337) |
| AR(1) | -0.0322 | 0.0156 | 0.1194*** | 0.0656*** | 0.0926*** | 0.1178*** | 0.0823*** |
| | (0.0177) | (0.0206) | (0.0198) | (0.0211) | (0.0224) | (0.0203) | (0.0207) |
| Const. (V) | 0.1551*** | 0.1643 | 0.3146** | 0.1951 | 0.3295*** | 0.6334*** | 0.2538*** |
| | (0.0520) | (0.0324) | (0.1495) | (0.1156) | (0.0904) | (0.2694) | (0.0818) |
| d-FIGARCH | 0.2894*** | 0.3351*** | 0.2126*** | 0.4548*** | 0.2850*** | 0.4236*** | 0.2395*** |
| | (0.0492) | (0.0432) | (0.0619) | (0.0711) | (0.0623) | (0.0630) | (0.0495) |
| ARCH | 0.0926 | 0.2529*** | 0.0066 | 0.0907 | 0.1041 | 0.3127*** | 0.1244 |
| | (0.1840) | (0.0716) | (0.1313) | (0.0894) | (0.0644) | (0.0689) | (0.1554) |
| GARCH | 0.3392*** | 0.4916*** | 0.1275 | 0.4056*** | 0.4420*** | 0.6032*** | 0.2796 |
| | (0.0218) | (0.0845) | (0.1255) | (0.1203) | (0.0761) | (0.0916) | (0.1728) |
| APARCH | 0.9878*** | 0.7035*** | 0.9480*** | 0.2389*** | 0.5388*** | 0.2662*** | 0.6794*** |
| ($\lambda$) | (0.0545) | (0.1548) | (0.0559) | (0.0764) | (0.1964) | (0.0672) | (0.2296) |
| APARCH | 1.2578*** | 1.3789*** | 1.2660*** | 1.5888*** | 1.4397*** | 1.7701*** | 1.3539*** |
| ($\delta$) | (0.1117) | (0.1204) | (0.2000) | (0.2249) | (0.1751) | (0.1530) | (0.1957) |
| Panel B: Estimates of the DECO process | | | | | | | |
| Average | 0.3151*** | | | | | | |
| CORij | (0.0260) | | | | | | |
| $\alpha_{DECO}$ | 0.0138*** | | | | | | |
| | (0.0043) | | | | | | |
| $\beta_{DECO}$ | 0.9782*** | | | | | | |
| | (0.0068) | | | | | | |
| Panel C: Diagnostic tests | | | | | | | |
| Q(20) | 61.218 | 61.163 | 43.825 | 17.664 | 18.595 | 33.485 | 27.320 |
| | [0.0000] | [0.0000] | [0.002] | [0.6094] | [0.5482] | [0.0298] | [0.1264] |
| $Q^2(20)$ | 21.809 | 8.5859 | 13.907 | 10.499 | 8.0650 | 9.7560 | 15.571 |
| | [0.3509] | [0.9872] | [0.8351] | [0.9581] | [0.9914] | [0.9723] | [0.7428] |

Notes: See notes of Table 2.

**Table 5:** Estimation of the AR(1)-FIAPARCH(1,$d$,1)-DECO model in the post-crisis period

| | U.S. | Europe | Brazil | Russia | India | China | S. Africa |
|---|---|---|---|---|---|---|---|
| Panel A: Estimates of the conditional mean and variance equations. | | | | | | | |
| Const. (M) | 0.0260 | 0.0399 | -0.0659 | -0.0556 | 0.0092 | -0.0098 | -0.0352 |
| | (0.0140) | (0.0260) | (0.0403) | (0.0412) | (0.0338) | (0.0324) | (0.0257) |
| AR(1) | -0.0437*** | -0.0140 | 0.0452** | 0.0575** | 0.0737*** | 0.0393 | -0.0043*** |
| | (0.0126) | (0.0229) | (0.0224) | (0.0244) | (0.0281) | (0.0225) | (0.0224) |
| Const. (V) | 0.0478 | 0.1383 | 0.0836 | 0.1216 | 0.0807** | 0.1124** | 0.0806*** |
| | (0.1283) | (0.1698) | (0.0499) | (0.1234) | (0.0324) | (0.0513) | (0.0733) |
| d-FIGARCH | 0.4052*** | 0.6750*** | 0.4173*** | 0.3353*** | 0.5340*** | 0.4142*** | 0.3477*** |
| | (0.0678) | (0.1555) | (0.0964) | (0.0980) | (0.1597) | (0.1303) | (0.0904) |
| ARCH | 0.1958** | 0.0718 | 0.1509*** | 0.1253 | 0.1935** | 0.0895 | 0.3313*** |
| | (0.0697) | (0.0590) | (0.0751) | (0.1758) | (0.0950) | (0.0727) | (0.0630) |
| GARCH | 0.5229*** | 0.7148*** | 0.5459*** | 0.4179** | 0.6772*** | 0.4746*** | 0.6135*** |
| | (0.0632) | (0.1397) | (0.0970) | (0.2078) | (0.0858) | (0.1572) | (0.0773) |
| APARCH | 0.9999*** | 0.4703** | 0.5244*** | 0.6080** | 0.4646** | 0.2705** | 0.9999*** |
| ($\lambda$) | (0.0777) | (0.1341) | (0.1620) | (0.2539) | (0.2206) | (0.1341) | (0.0764) |
| APARCH | 1.2806*** | 1.6345*** | 1.6406*** | 1.6597*** | 1.4907*** | 1.7914*** | 1.3306*** |
| ($\delta$) | (0.1040) | (0.1439) | (0.1535) | (0.1946) | (0.2162) | (0.1439) | (0.1751) |
| Panel B: Estimates of the DECO process | | | | | | | |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| Average CORij | $0.6326^{***}$ (0.0392) | | | | | | |
| $\alpha_{DECO}$ | $0.0121^{**}$ (0.0053) | | | | | | |
| $\beta_{DECO}$ | $0.9871^{***}$ (0.0073) | | | | | | |
| Panel C: Diagnostic tests | | | | | | | |
| Q(20) | 65.969 [0.0000] | 36.072 [0.0150] | 43.879 [0.0015] | 21.305 [0.3793] | 34.736 [0.0215] | 76.104 [0.0000] | 33.311 [0.0311] |
| $Q^2(20)$ | 27.299 [0.1270] | 22.366 [0.3209] | 29.571 [0.0771] | 5.8901 [0.9990] | 11.647 [0.9276] | 11.745 [0.9245] | 21.288 [0.3803] |

Notes: See notes of Table 2.

*3.4 VaR forecasting analysis*

We now evaluate the performance of the normal, Student-t and skewed Student-t DECO-FIAPARCH $(1,d,1)$ models for estimating the one-day-ahead VaRs over both the in-sample and out-of-sample periods. Different significance levels ($\alpha$) ranging from 0.05 to 0.0025 are considered and the Kupiec test is used to test the accuracy of the VaR models in use.

Tables 6-7 report the in-sample VaR analysis for the short and long trading positions, respectively. The results for the short trading positions show that the DECO-FIAPARCH models with normal and Student-t distributions provide poor performance for the estimation of VaRs as the null hypothesis that the empirical failure rate is equal to the pre-determined VaR confidence level is rejected in 19 out of 35 cases (for the DECO-FIAPARCH with normal distribution) and in 16 out of 35 cases (for the DECO-FIAPARCH with Student-t distribution) at the 5% level. On the other hand, the accuracy of the DECO-FIAPARCH with the skewed Student-t distribution is rejected in only four out of 35 cases at the 5% level. Very similar results are obtained for the long trading positions. Altogether, the in-sample results suggest that the VaR models are misspecified with the normal and Student-t distributions. By contrast, investors and portfolio managers can build a more accurate risk management strategy for portfolios involving the developed and BRICS stock markets by using the skewed Student-t DECO-FIAPARCH $(1,d,1)$ model to compute the in-sample VaR. This superior performance is fully supported by the leptokurtic behavior of stock market returns, volatility persistence and long memory.

Tables 8-9 report the out-of-sample one-day ahead VaR results as well as their associated failure rates and corresponding Kupiec LR tests for the both short and long trading positions. Similar to the in-sample analysis, we generally find that the DECO-FIAPARCH model with the skewed Student-t distribution performs better than the ones with normal and Student-t distributions in generating the VaRs for long and short trading positions, regardless of the market under consideration.

**Table 6:** In-sample VaR analysis (the short trading positions case)

| | **U.S.** | | **Europe** | | **Brazil** | | **Russia** | | **India** | | **China** | | **S.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 | Failure rate | Kupiec LRT |
| FIAPARCH model – normal distribution | | | | | | | | | | | | | | |
| 0.9500 | 0.9637 | 20.046 [0.000] | 0.9618 | 14.486 [0.000] | 0.9582 | 6.9631 [0.008] | 0.9613 | 13.383 [0.000] | 0.9624 | 16.229 [0.000] | 0.9560 | 3.7051 [0.054] | 0.9585 | 7.3484 [0.007] |
| 0.9750 | 0.9837 | 16.314 [0.000] | 0.9784 | 2.3804 [0.122] | 0.9804 | 6.0183 [0.014] | 0.9776 | 1.3155 [0.251] | 0.9809 | 7.0727 [0.007] | 0.9751 | 0.0069 [0.933] | 0.9791 | 3.3975 [0.065] |
| 0.9900 | 0.9934 | 6.0968 [0.013] | 0.9921 | 2.1792 [0.139] | 0.9912 | 0.7123 [0.398] | 0.9881 | 1.4946 [0.221] | 0.9894 | 0.1308 [0.717] | 0.9850 | 9.7068 [0.001] | 0.9885 | 0.8822 [0.347] |
| 0.9950 | 0.9967 | 3.0349 [0.081] | 0.9953 | 0.1427 [0.705] | 0.9945 | 0.2117 [0.645] | 0.9925 | 4.8252 [0.028] | 0.9925 | 4.8252 [0.028] | 0.9901 | 16.949 [0.000] | 0.9938 | 1.1223 [0.289] |
| 0.9975 | 0.9989 | 4.5532 [0.032] | 0.9973 | 0.0324 [0.857] | 0.9971 | 0.2188 [0.639] | 0.9942 | 13.752 [0.000] | 0.9947 | 10.596 [0.001] | 0.9934 | 20.972 [0.000] | 0.9949 | 9.1417 [0.002] |
| FIAPARCH model – Student-t distribution | | | | | | | | | | | | | | |
| 0.9500 | 0.9593 | 9.0007 [0.002] | 0.9604 | 11.320 [0.001] | 0.9574 | 5.5311 [0.018] | 0.9563 | 3.9830 [0.045] | 0.9585 | 7.3484 [0.006] | 0.9519 | 0.3582 [0.549] | 0.9571 | 5.2001 [0.022] |
| 0.9750 | 0.9852 | 23.168 [0.000] | 0.9793 | 3.7792 [0.051] | 0.9815 | 8.8307 [0.002] | 0.9798 | 4.6080 [0.031] | 0.9813 | 8.2208 [0.004] | 0.9776 | 1.3155 [0.251] | 0.9811 | 7.6349 [0.005] |
| 0.9900 | 0.9964 | 25.814 [0.000] | 0.9942 | 10.028 [0.001] | 0.9938 | 7.9183 [0.004] | 0.9925 | 3.2430 [0.071] | 0.9923 | 2.6823 [0.101] | 0.9901 | 0.0067 [0.934] | 0.9931 | 5.2878 [0.021] |
| 0.9950 | 0.9991 | 23.713 [0.000] | 0.9975 | 7.569 [0.005] | 0.9975 | 7.5697 [0.005] | 0.9962 | 1.6141 [0.203] | 0.9962 | 1.6141 [0.203] | 0.9949 | 0.0022 [0.962] | 0.9956 | 0.3544 [0.551] |
| 0.9975 | 1.0000 | .NaN | 0.9986 | 3.0923 [0.078] | 0.9989 | 4.5532 [0.032] | 0.9986 | 3.0923 [0.078] | 0.9982 | 1.1283 [0.288] | 0.9978 | 0.1768 [0.674] | 0.9984 | 1.9667 [0.160] |
| FIAPARCH model – skewed Student-t distribution | | | | | | | | | | | | | | |
| 0.9500 | 0.9512 | 0.1540 [0.694] | 0.9552 | 2.6977 [0.100] | 0.9499 | 0.0002 [0.986] | 0.9525 | 0.6487 [0.420] | 0.9525 | 0.6487 [0.420] | 0.9514 | 0.2125 [0.644] | 0.9492 | 0.0486 [0.825] |
| 0.9750 | 0.9791 | 3.3975 [0.065] | 0.9760 | 0.2170 [0.641] | 0.9767 | 0.5715 [0.449] | 0.9773 | 1.0999 [0.294] | 0.9787 | 2.6983 [0.100] | 0.9771 | 0.9041 [0.341] | 0.9756 | 0.0750 [0.784] |
| 0.9900 | 0.9927 | 3.8629 [0.049] | 0.9929 | 4.5439 [0.033] | 0.9912 | 0.7123 [0.398] | 0.9912 | 0.7123 [0.398] | 0.9916 | 1.3396 [0.247] | 0.9899 | 0.0044 [0.946] | 0.9888 | 0.6341 [0.425] |
| 0.9950 | 0.9980 | 10.880 [0.001] | 0.9962 | 1.6141 [0.203] | 0.9958 | 0.6666 [0.414] | 0.9953 | 0.1427 [0.705] | 0.9949 | 0.0022 [0.962] | 0.9950 | 0.0022 [0.962] | 0.9947 | 0.0650 [0.798] |
| 0.9975 | 0.9993 | 8.7870 [0.003] | 0.9982 | 1.1283 [0.288] | 0.9982 | 1.1283 [0.288] | 0.9982 | 1.1283 [0.288] | 0.9982 | 1.1283 [0.288] | 0.9978 | 0.1768 [0.674] | 0.9971 | 0.2188 [0.639] |

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.

**Table 7:** In-sample VaR analysis (the long trading positions case)

| | **U.S.** | | **Europe** | | **Brazil** | | **Russia** | | **India** | | **China** | | **S.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 | Failure rate | Kupiec LRT |
| FIAPARCH model – normal distribution | | | | | | | | | | | | | | |
| 0.0500 | 0.0575 | 5.1821 [0.022] | 0.0601 | 9.3101 [0.002] | 0.0518 | 0.3110 [0.577] | 0.0474 | 0.6487 [0.420] | 0.0524 | 0.5760 [0.447] | 0.0504 | 0.0233 [0.878] | 0.0562 | 3.5524 [0.059] |
| 0.0250 | 0.0373 | 24.699 [0.000] | 0.0362 | 20.719 [0.000] | 0.0298 | 4.1550 [0.041] | 0.0316 | 7.5518 [0.005] | 0.0283 | 1.9770 [0.159] | 0.0298 | 4.1550 [0.041] | 0.0302 | 4.9153 [0.026] |
| 0.0100 | 0.0180 | 23.812 [0.000] | 0.0186 | 27.499 [0.000] | 0.0169 | 18.169 [0.000] | 0.0191 | 30.077 [0.000] | 0.0155 | 12.273 [0.000] | 0.0153 | 11.389 [0.000] | 0.0162 | 15.098 [0.000] |
| 0.0050 | 0.0105 | 21.262 [0.000] | 0.0105 | 21.262 [0.000] | 0.0100 | 18.343 [0.000] | 0.0129 | 40.161 [0.000] | 0.0096 | 15.600 [0.000] | 0.0103 | 19.781 [0.000] | 0.0107 | 22.785 [0.000] |
| 0.0025 | 0.0085 | 40.965 [0.000] | 0.0050 | 9.1417 [0.000] | 0.0079 | 33.781 [0.000] | 0.0085 | 40.965 [0.000] | 0.0070 | 24.995 [0.000] | 0.0054 | 12.134 [0.000] | 0.0068 | 22.951 [0.000] |
| FIAPARCH model – Student-t distribution | | | | | | | | | | | | | | |
| 0.0500 | 0.0638 | 17.063 [0.000] | 0.0625 | 14.078 [0.000] | 0.0553 | 2.6311 [0.104] | 0.0537 | 1.3436 [0.246] | 0.0599 | 8.9227 [0.002] | 0.0557 | 3.0751 [0.079] | 0.0605 | 10.108 [0.001] |
| 0.0250 | 0.0364 | 21.490 [0.000] | 0.0342 | 14.354 [0.000] | 0.0289 | 2.8170 [0.093] | 0.0305 | 5.3180 [0.021] | 0.0270 | 0.7311 [0.392] | 0.0274 | 1.0810 [0.298] | 0.0296 | 3.7975 [0.051] |
| 0.0100 | 0.0114 | 0.8822 [0.347] | 0.0133 | 4.7847 [0.028] | 0.0116 | 1.1693 [0.279] | 0.0140 | 6.7049 [0.009] | 0.0105 | 0.1308 [0.717] | 0.0107 | 0.2575 [0.611] | 0.0129 | 3.6699 [0.055] |
| 0.0050 | 0.0070 | 3.3334 [0.067] | 0.0050 | 0.0022 [0.962] | 0.0070 | 3.3334 [0.067] | 0.0054 | 0.2117 [0.645] | 0.0059 | 0.7433 [0.388] | 0.0030 | 3.9420 [0.047] | 0.0063 | 1.5732 [0.209] |
| 0.0025 | 0.0041 | 4.2408 [0.039] | 0.0021 | 0.1768 [0.674] | 0.0026 | 0.0324 [0.857] | 0.0024 | 0.0133 [0.907] | 0.0037 | 2.4056 [0.120] | 0.0006 | 8.7870 [0.003] | 0.0032 | 1.0439 [0.306] |
| FIAPARCH model – skewed Student-t distribution | | | | | | | | | | | | | | |
| 0.0500 | 0.0583 | 6.4309 [0.011] | 0.0555 | 2.8489 [0.091] | 0.0491 | 0.0653 [0.798] | 0.0496 | 0.0141 [0.905] | 0.0535 | 1.1939 [0.274] | 0.0551 | 2.4218 [0.119] | 0.0507 | 0.0486 [0.825] |
| 0.0250 | 0.0298 | 4.1550 [0.041] | 0.0289 | 2.8170 [0.093] | 0.0263 | 0.3321 [0.564] | 0.0281 | 1.7288 [0.188] | 0.0228 | 0.9041 [0.341] | 0.0270 | 0.7311 [0.392] | 0.0245 | 0.0318 [0.858] |
| 0.0100 | 0.0094 | 0.1469 [0.701] | 0.0098 | 0.0067 [0.934] | 0.0094 | 0.1469 [0.701] | 0.0118 | 1.4946 [0.221] | 0.0094 | 0.1469 [0.701] | 0.0105 | 0.1308 [0.717] | 0.0090 | 0.4750 [0.490] |
| 0.0050 | 0.0054 | 0.2117 [0.645] | 0.0037 | 1.6141 [0.203] | 0.0039 | 1.0845 [0.297] | 0.0048 | 0.0268 [0.869] | 0.0050 | 0.0022 [0.962] | 0.0030 | 3.9420 [0.047] | 0.0039 | 1.0845 [0.297] |
| 0.0025 | 0.0030 | 0.5596 [0.454] | 0.0017 | 1.1283 [0.288] | 0.0024 | 0.0133 [0.907] | 0.0021 | 0.1768 [0.674] | 0.0026 | 0.0324 [0.857] | 0.0006 | 8.7870 [0.003] | 0.0030 | 0.5596 [0.454] |

Notes: See notes of Table 6.

**Table 8:** Out-of-sample VaR analysis (the short trading positions case)

| | **U.S.** | | **Europe** | | **Brazil** | | **Russia** | | **India** | | **China** | | **S.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 | Failure rate | Kupiec LRT |
| FIAPARCH model – normal distribution | | | | | | | | | | | | | | |
| 0.9500 | 0.9650 | 6.7128 [0.009] | 0.9674 | 9.1778 [0.002] | 0.9666 | 8.3072 [0.003] | 0.9706 | 13.177 [0.000] | 0.9714 | 14.312 [0.000] | 0.9714 | 14.312 [0.000] | 0.9738 | 18.068 [0.000] |
| 0.9750 | 0.9857 | 7.0016 [0.008] | 0.9825 | 3.2797 [0.070] | 0.9857 | 7.0016 [0.008] | 0.9825 | 3.2797 [0.070] | 0.9881 | 10.963 [0.000] | 0.9825 | 3.2797 [0.070] | 0.9865 | 8.2002 [0.004] |
| 0.9900 | 0.9952 | 4.3316 [0.037] | 0.9912 | 0.2144 [0.643] | 0.9944 | 2.9961 [0.083] | 0.9873 | 0.8538 [0.355] | 0.9944 | 2.9961 [0.083] | 0.9888 | 0.1516 [0.696] | 0.9928 | 1.1539 [0.282] |
| 0.9950 | 0.9976 | 2.1571 [0.141] | 0.9928 | 1.0260 [0.311] | 0.9960 | 0.2902 [0.590] | 0.9928 | 1.0260 [0.311] | 0.9944 | 0.0754 [0.783] | 0.9928 | 1.0260 [0.311] | 0.9952 | 0.0145 [0.903] |
| 0.9975 | 0.9992 | 2.0089 [0.156] | 0.9960 | 0.9230 [0.336] | 0.9968 | 0.2117 [0.645] | 0.9960 | 0.9230 [0.336] | 0.9976 | 0.0072 [0.932] | 0.9944 | 3.4909 [0.061] | 0.9960 | 0.9230 [0.336] |
| FIAPARCH model – Student-t distribution | | | | | | | | | | | | | | |
| 0.9500 | 0.9603 | 3.0295 [0.081] | 0.9682 | 10.099 [0.001] | 0.9658 | 7.4859 [0.006] | 0.9698 | 12.097 [0.000] | 0.9674 | 9.1778 [0.002] | 0.9674 | 9.1778 [0.002] | 0.9738 | 13.177 [0.000] |
| 0.9750 | 0.9857 | 7.0016 [0.008] | 0.9873 | 9.5180 [0.002] | 0.9888 | 12.542 [0.000] | 0.9825 | 3.2797 [0.070] | 0.9888 | 12.542 [0.000] | 0.9841 | 4.9371 [0.026] | 0.9888 | 8.2002 [0.000] |
| 0.9900 | 0.9976 | 10.663 [0.001] | 0.9928 | 1.1539 [0.282] | 0.9952 | 4.3316 [0.037] | 0.9936 | 1.9489 [0.162] | 0.9944 | 2.9961 [0.083] | 0.9912 | 0.2144 [0.643] | 0.9944 | 2.9961 [0.083] |
| 0.9950 | 0.9992 | 6.9413 [0.008] | 0.9960 | 0.2902 [0.590] | 0.9976 | 2.1571 [0.141] | 0.9976 | 2.1571 [0.141] | 0.9984 | 4.0251 [0.044] | 0.9960 | 0.2902 [0.590] | 0.9960 | 0.2902 [0.590] |
| 0.9975 | 1.0000 | .NaN [0.000] | 0.9968 | 0.2117 [0.645] | 0.9984 | 0.4840 [0.008] | 0.9992 | 2.0089 [0.156] | 0.9992 | 2.0089 [0.156] | 0.9984 | 0.4840 [0.486] | 0.9992 | 2.0089 [0.156] |
| FIAPARCH model – skewed Student-t distribution | | | | | | | | | | | | | | |
| 0.9500 | 0.9563 | 1.1152 [0.290] | 0.9619 | 4.0816 [0.043] | 0.9619 | 4.0816 [0.043] | 0.9611 | 3.5343 [0.060] | 0.9634 | 5.3069 [0.021] | 0.9674 | 9.1778 [0.002] | 0.9658 | 7.4859 [0.006] |
| 0.9750 | 0.9793 | 1.0463 [0.306] | 0.9801 | 1.4787 [0.223] | 0.9833 | 4.0600 [0.043] | 0.9825 | 3.2797 [0.070] | 0.9873 | 9.5180 [0.002] | 0.9841 | 4.9371 [0.026] | 0.9849 | 5.9159 [0.015] |
| 0.9900 | 0.9952 | 4.3316 [0.037] | 0.9904 | 0.0293 [0.864] | 0.9944 | 2.9961 [0.083] | 0.9920 | 1.9489 [0.445] | 0.9944 | 2.9961 [0.083] | 0.9912 | 0.2144 [0.643] | 0.9928 | 1.1539 [0.282] |
| 0.9950 | 0.9976 | 2.1571 [0.141] | 0.9928 | 1.0260 [0.311] | 0.9960 | 0.2902 [0.590] | 0.9960 | 0.2902 [0.590] | 0.9984 | 4.0251 [0.044] | 0.9960 | 0.2902 [0.590] | 0.9960 | 0.2902 [0.590] |
| 0.9975 | 0.9992 | 2.0089 [0.156] | 0.9960 | 0.9230 [0.336] | 0.9976 | 0.0072 [0.932] | 0.9992 | 2.0089 [0.156] | 0.9992 | 2.0089 [0.156] | 0.9984 | 0.4840 [0.486] | 0.9968 | 0.2117 [0.645] |

Notes: see notes of Table 6.

**Table 9:** Out-of-sample VaR analysis (the long trading positions case)

| | **U.S.** | | **Europe** | | **Brazil** | | **Russia** | | **India** | | **China** | | **S.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 | Failure rate | Kupiec LRT |
| FIAPARCH model – normal distribution | | | | | | | | | | | | | | |
| 0.0500 | 0.0587 | 1.9191 [0.165] | 0.0563 | 1.0290 [0.310] | 0.0444 | 0.8491 [0.356] | 0.0468 | 0.2728 [0.601] | 0.0523 | 0.1481 [0.700] | 0.0531 | 0.2621 [0.608] | 0.0555 | 0.7914 [0.373] |
| 0.0250 | 0.0357 | 5.2496 [0.021] | 0.0349 | 4.5374 [0.033] | 0.0301 | 1.2919 [0.255] | 0.0277 | 0.3852 [0.534] | 0.0277 | 0.3852 [0.534] | 0.0309 | 1.7047 [0.191] | 0.0325 | 2.6876 [0.101] |
| 0.0100 | 0.0222 | 14.107 [0.000] | 0.0190 | 8.2336 [0.004] | 0.0134 | 1.3991 [0.236] | 0.0174 | 5.7942 [0.016] | 0.0111 | 0.1516 [0.696] | 0.0174 | 5.7942 [0.016] | 0.0142 | 2.0637 [0.150] |
| 0.0050 | 0.0142 | 14.503 [0.000] | 0.0095 | 4.0905 [0.043] | 0.0023 | 2.1571 [0.141] | 0.0119 | 8.6855 [0.003] | 0.0071 | 1.0260 [0.311] | 0.0095 | 4.0905 [0.043] | 0.0079 | 1.8516 [0.173] |
| 0.0025 | 0.0111 | 20.160 [0.000] | 0.0079 | 9.4411 [0.002] | 0.0015 | 0.4840 [0.486] | 0.0071 | 7.2241 [0.007] | 0.0055 | 3.4909 [0.061] | 0.0055 | 3.4909 [0.061] | 0.0039 | 0.9230 [0.337] |
| FIAPARCH model – Student-t distribution | | | | | | | | | | | | | | |
| 0.0500 | 0.0634 | 4.4653 [0.034] | 0.0531 | 0.2621 [0.608] | 0.0476 | 0.1526 [0.695] | 0.0555 | 0.7914 [0.373] | 0.0603 | 2.6567 [0.103] | 0.0563 | 1.0290 [0.310] | 0.0603 | 2.6567 [0.103] |
| 0.0250 | 0.0380 | 7.6591 [0.005] | 0.0317 | 2.1703 [0.140] | 0.0269 | 0.1984 [0.655] | 0.0285 | 0.6307 [0.427] | 0.0301 | 1.2919 [0.255] | 0.0293 | 0.9335 [0.333] | 0.0317 | 2.1703 [0.140] |
| 0.0100 | 0.0150 | 2.8411 [0.091] | 0.0150 | 2.8411 [0.091] | 0.0031 | 8.0799 [0.004] | 0.0126 | 0.8538 [0.355] | 0.0087 | 0.2144 [0.643] | 0.0111 | 0.1516 [0.696] | 0.0119 | 0.4352 [0.509] |
| 0.0050 | 0.0103 | 5.4703 [0.019] | 0.0079 | 1.8516 [0.173] | 0.0007 | 6.9413 [0.008] | 0.0055 | 0.0754 [0.783] | 0.0031 | 0.9701 [0.324] | 0.0007 | 6.9413 [0.008] | 0.0039 | 0.2902 [0.590] |
| 0.0025 | 0.0071 | 7.2241 [0.007] | 0.0047 | 2.0388 [0.153] | 0.0000 | .NaN | 0.0015 | 0.4840 [0.486] | 0.0023 | 0.0072 [0.932] | 0.0000 | .NaN | 0.0007 | 2.0089 [0.156] |
| FIAPARCH model – skewed Student-t distribution | | | | | | | | | | | | | | |
| 0.0500 | 0.0595 | 2.2737 [0.131] | 0.0515 | 0.0661 [0.796] | 0.0428 | 1.4192 [0.233] | 0.0484 | 0.0675 [0.794] | 0.0587 | 1.9191 [0.165] | 0.0563 | 1.0290 [0.310] | 0.0515 | 0.0661 [0.796] |
| 0.0250 | 0.0333 | 3.2553 [0.071] | 0.0269 | 0.1984 [0.655] | 0.0222 | 0.4141 [0.519] | 0.0222 | 0.4141 [0.519] | 0.0230 | 0.2089 [0.647] | 0.0293 | 0.9335 [0.333] | 0.0246 | 0.0081 [0.927] |
| 0.0100 | 0.0134 | 1.3991 [0.236] | 0.0111 | 0.1516 [0.696] | 0.0023 | 10.663 [0.001] | 0.0079 | 0.5831 [0.445] | 0.0071 | 1.1539 [0.282] | 0.0111 | 0.1516 [0.696] | 0.0055 | 2.9961 [0.083] |
| 0.0050 | 0.0095 | 4.0905 [0.043] | 0.0063 | 0.4245 [0.514] | 0.0000 | .NaN | 0.0015 | 4.0251 [0.045] | 0.0031 | 0.9701 [0.324] | 0.0007 | 6.9413 [0.008] | 0.0023 | 2.1571 [0.141] |
| 0.0025 | 0.0039 | 0.9230 [0.336] | 0.0031 | 0.2117 [0.645] | 0.0000 | .NaN | 0.0007 | 2.0089 [0.156] | 0.0015 | 0.4840 [0.486] | 0.0000 | .NaN | 0.0007 | 2.0089 [0.156] |

Notes: See notes of Table 6.

## 4. Conclusions

We examine dynamic linkages of the BRICS markets with the U.S. and European markets, using the bivariate DECO-FIAPARCH model. We conduct a portfolio VaR analysis based on the obtained results with respect to three distributions and determine the implications of the results for portfolio managers and investors. Our results show evidence of the presence of leverage effects and fractional integration in conditional volatility for all markets. The market linkages at the group level, represented by the equicorrelation coefficient, change over time, with an increasing tendency after the onset of the GFC 2008-2009, which confirms certain degree of contagious effects across markets. When the Markov-switching dynamic regression is used to identify the potential structural change in the time-path of market return series, we find the existence of two regimes (stable versus volatile) for all markets, with a common break date on the 15$^{th}$ of September 2008 (breakpoint characterizing the entry into the global financial crisis) and significant effects of crisis on the estimated parameters of the DECO-FIAPARCH model. Another important finding is that the DECO-FIAPARCH model with the skewed Student-t distribution is the most suitable specification for assessing the portfolio's VaRs, over both the in-sample and out-of-sample periods. Altogether, these results suggest that global investors should have interest in holding diversified portfolios of stocks issued by the BRICS, the U.S., and Europe in order to improve the portfolio's risk-adjusted performance, while policymakers are able to build decoupling strategies to immunize their markets to harmful contagious effects from other markets.

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