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DECOUPLING AND THE SPILLOVER EFFECTS OF THE US FINANCIAL CRISIS: EVIDENCE FROM THE BRIC MARKETS

Decoupling and the spillover effects of the US financial crisis: Evidence from the BRIC markets

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Abstract

Even though the global contagion effects of the financial crisis have been well documented, the transmission mechanism as well as the nature of the volatility spillovers among the US, EU and the BRIC markets has not been systematically investigated. To examine the dynamic linear and nonlinear causal linkages a stepwise filtering methodology is introduced, for which vector autoregressions and various multivariate GARCH representations are adopted. The sample covers the after-Euro period and includes the financial crisis and the Eurozone debt crisis. The empirical results show that the BRICs have become more internationally integrated after the US financial crisis and contagion is further substantiated. Moreover, no consistent evidence in support of the "decoupling" view is found. Some nonlinear causal links persist after filtering during the examined period. This indicates that nonlinear causality can, to a large extent, be explained by simple volatility effects, although tail dependency and higher-moments may be significant factors of the remaining interdependences.

Keywords: stock markets; nonlinear causality; filtering; GJR-GARCH; multivariate GARCH models; spillovers

JEL classification: C14; C58; G15; C51; C52

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1. INTRODUCTION

The global financial crisis of 2007-2010 and the subsequent Eurozone sovereign debt crisis served as a catalyst towards further investigation of the spillover effects among the US, Eurozone and Asian stock markets. These interdependencies could provide evidence whether there is a seemingly growing integration in international markets with important implications for portfolio diversification. Only a limited number of studies are available on the contagion effects of the US subprime crisis and its repercussions. Angkinand *et al.* (2010) explored the spillovers from the US financial crisis to many developed economies by utilizing a structural vector autoregressive framework, and their results indicated that the interdependences increased dramatically when crisis emerged. Additionally, Yilmaz (2010) investigated the extent of contagion across Southeast Asian equity markets and found evidence of direct linkages among them by means of variance decomposition analysis of the stock returns. Fidrmuc and Korhonen (2010) investigated the transmission of the subprime crisis to China and India, with the application of dynamic correlations, and concluded that it had a significant effect on their business cycles.

Moreover, a growing interest is developing with regard to the spillover effects between the four emerging markets of Brazil, Russia, China and India and the US and Eurozone markets. According to Wilson and Purushothaman (2003) the four emerging markets, also called the BRICs, are the key performers in the world economy in the last two decades and would become the dominant economies within the next forty years. They encompass over 25% of the world's land coverage and 40% of the world's population and hold a combined GDP of 18.486 trillion dollars. The importance of the BRICs has been recognized as they currently influence economic developments in other developed and emerging countries. The BRICs' engine of growth is the rising Chinese economy, due to its export driven policy and the accumulated foreign investment from the developed countries, while India, Russia and Brazil seem to closely follow the pace of the Chinese economy. The magnitude of their growth has altered the share of economic performance globally. In the period 1988-2008, the BRICs GDP share in the world economy increased overall from 7% to 15%, while among the countries Chinese GDP raised from 1.7% to 7.1% and Brazil and Russia contributed 2.7 % each. According to recent statistics by the World Bank, the GDP of China in 2005 was $5.3 trillion, compared to $2.2 trillion using market exchange rates. Brazil and Russia produce more than India, but the latter is expected to grow at the rate of 5% per year for the next thirty years. Tarzi (2000, 2005) studied the flow of foreign portfolio equity investments and foreign direct investment to emerging markets between 1986 and 1995 and reported that stock market capitalization in emerging countries grew from $171 billion to 1.9 trillion and the market share held in capitalization increased from 4% to 11%, mostly attributed to the BRICs. In the 1990s the foreign investment increased from 7% to 21% as a GDP ratio in the developing countries, most of which flew into Brazil, China, and India. Moreover, Russia after the fall of the Soviet Union and the crisis of 1997 has achieved price stability with a dropping inflation from 215% in 1994 to 8.3% in 1998, and now is considered as an attractive market for asset diversification. Finally, a massive increase is observed in the BRIC stock market indices mostly during the last decade. Indicatively, Brazil's Bovespa Index rose by 342%, China's Shanghai Composite Index by 75%, India's Sensex Index by 250% and Russia's Micex Index increased by 638%. This evidence further substantiates their key role in the future of global economy.

Causal links among stock markets could have important implications for hedging, trading strategies and financial market regulations. The presence of long-term linear and nonlinear relationships may be utilized to achieve gains from international portfolio diversification as well as to reduce systematic market risk. The recent empirical evidence is invariably based on the linear Granger causality test (Granger, 1969). But, as noted by Hsieh (1989, 1991) and many others, financial time series exhibit significant nonlinear features. Hiemstra and Jones (1994) claim that a nonlinear nonparametric Granger causality test based on the work of Baek and Brock (1992) may be more effective in revealing nonlinear causal relationships in stock prices. In the present study a multistep filtering methodology is applied for examining dynamic relationships. First, the linear and nonlinear dynamic linkages between the US, European and BRIC stock markets, are explored via the parametric Granger causality test and the modified Baek-Brock test. Then, after VAR filtering of the return series, the residuals are examined by the modified Baek-Brock causality test. This step ensures that any remaining causality is strictly nonlinear in nature, as the VAR model has already purged the residuals of linear causality. Finally, in the last step, the hypothesis of nonlinear non-causality is tested after controlling for conditional heteroskedasticity in the data using many specifications of multivariate GARCH models such as with asymmetric impact of unconditional shocks or a conditional correlation matrix. This approach allows capturing the short-run movements and the volatility spillover mechanism, assuming that spillovers are realizations of international news affecting the global equity markets.

The aim of the study is to test for the existence of both linear and nonlinear causal relationships among the US, European and the BRIC stock markets. The investigated time period starts from the introduction of Euro and covers diverse regimes including the rise and fall of the tech-market bubble and the financial crisis of 2007-2010. It also includes the EU debt crisis, associated with the widening of bond yield spreads and the rise of credit default swaps, concerning Eurozone countries such as Greece, Ireland and Portugal. This crisis had a significant effect on the global stock markets. In that context, it is worth investigating whether these crises may have changed the direction and strength of the causal relationships among the examined markets. To enhance robustness in the results, the total period is further segmented into disjoint sub-periods.

Overall, this paper contributes to the literature in international volatility spillovers and interdependencies by focusing on the BRIC markets that have thus far received minor attention in previous empirical studies. It examines the transmission of the US subprime crisis to the BRIC economies and investigates, through the analysis of their equity markets, as to what extent these markets have been affected by the crisis. This study also investigates the impact of the Eurozone sovereign debt crisis on the linkages between the Euro area and the BRICs by using the German financial market as a proxy for the Eurozone. Currently, the BRIC stock markets are of great interest to international portfolio managers as they are affected by the currency markets due to global trade competitiveness. Specifically, the financial markets of US, Germany, China and India are linked via the currency markets and trade and investment agreements. The trade links of the US and Eurozone with Russia and Brazil are rather small, albeit their stock markets are interrelated through the global oil and energy demand.

Beyond the contagious affects of the US crisis on the BRICs, the present study also explores the so called "decoupling" phenomenon. This is based on the assumption that the emerging markets are now the major drivers of world economic growth as opposed to the US economy. However many recent studies, e.g., Frank and Hesse (2009), Dooley and Hutchison (2009) and Pula and Peltonen (2009), found no support for the decoupling view. As the BRIC economies have the fastest growing markets, it would be interesting to see whether empirical evidence supports the decoupling assumption. In general, the improved knowledge of the direction of interdependencies and volatility spillovers before and after the financial crisis could provide valuable information to international portfolio managers, multinational corporations and policymakers in managing their financial risks.

The paper develops as follows: section 2 provides a detailed overview of the literature on global market integration and spillovers. The employed causality tests are analyzed in section 3. The multivariate stepwise filtering methodology is introduced in section 4. Section 5 describes the data and provides a preliminary statistical analysis. Section 6 presents the empirical results and section 7 the economic and policy implications. Finally, section 8 provides the concluding remarks.

2. LITERATURE REVIEW

The literature on stock market interrelationships and integration is fairly rich. Since the beginning of 90s, the deregulation of capital movements lead to a systematic interrelation of the major financial markets. This dependence indicated a growing similarity in reactions towards macroeconomic policies or financial crises. However, the empirical evidence is diverse depending on the data, methodology and theoretical models used. Some previous works by Arshanapalli and Doukas (1993) and Hamao *et al.* (1990) showed that international stock markets are strongly integrated. On the contrary, Roca (1999) and Smyth and Nandha (2003) showed that global markets are weakly interlinked. Moreover, the majority of studies indicate that the US market leads other developed markets (King and Wadhwani, 1990). Yet, there is substantially less literature on stock market linkages between developed markets and emerging markets and very few concerning the BRIC economies (Garza-García and Vera-Juárez, 2010). Most of the spillover studies for the emerging markets have been conducted for Central and Eastern Europe (Gilmore, and McManus, 2002; Gündüz and Hatemi, 2005), Latin America and Asian countries (Choudhry, 1997; Christofi and Pericli, 1999; Chen *et al*., 2002).

Lee *et al.* (2004) investigate the linkages between the daily returns and volatility of the NASDAQ and Asian markets using EGRARCH and VAR-based methodology, and found strong evidence of volatility spillovers from the US to Asia. Hamao *et al.* (1990) studied the short-term interdependence of price returns and volatilities across the Tokyo, London, and New York stock markets. Shiller *et al.* (1991) reported that Japanese market participants are in general affected by trading in New York, but not vice versa. Bennett and Kelleher (1988), Hamao, *et al.* (1990) and Susmel and Engle (1990) showed that US returns appear to cause the other countries and that lagged spillovers of price volatility are found between the major markets. Global contagion was observed during the October 1987 crash in New York, according to King and Wadhwasi (1990). Rivas *et al.* (2006), who studied the response of the Latin American stock markets against European stock market movements via the application of a VAR model for the period 1990-1998, reported variations depending on the degree of investment allocation of the European country to Latin America. Moreover, using the Baek-Brock nonparametric causality test, Hunter (2003) examined the interdependencies of the emerging markets of Argentina, Chile, and Mexico. Using the same nonlinear test Ozdemir and Cakan (2007) examined the dynamic linkages among the stock market indices of the US, Japan, France and the UK and found that there is a strong bidirectional causal relationship between the US and the other countries. Dornau (1998) and Peiro *et al.* (1998) using simple linear causality tests, analyzed information transmission among the US, Japanese and German stock markets, while Baur and Jung (2006) examined the spillover effects between the US and German stock markets. The latter found that both market returns have a contemporaneous effect on each other, but that there are no lagged spillovers from the previous day.

Some studies have dealt with the lead–lag relationships among Asian markets and the nature of interdependencies with the developed economies. For instance, Phylaktis and Ravazzolo (2003) found no linkages or interactions among many Asian Pacific-Basin stock markets and Japan and US for the period 1980–1998. Najand (1996) used linear state space models and detected statistically significant linkages among the stock markets of Japan, Hong Kong and Singapore after the 1987 US stock market crash. In addition, an increase in stock market interdependence after the 1987 crisis was reported by Arshanapalli *et al.* (1995) for the emerging markets of Malaysia, Philippines, Thailand and the developed markets of Hong Kong, Singapore, the US and Japan for the period 1986–1992. Sheng and Tu (2000) investigated interrelations among 11 major stock markets in the Asian-Pacific region and the US in the pre- and post-Asian crisis period in 1997-1998 via the utilization of multivariate cointegration and error-correction models. They showed that long-run cointegration relationships emerged during and not before the period of the financial crisis. Finally, Weber (2007) revealed volatility causality among the Asian-Pacific region markets for the period 1999–2006. Eventually, as there is substantially less literature on stock market linkages between the developed markets and the BRIC economies, it should be interesting to examine the nature and direction of causality among them.

3. CAUSALITY TESTING

The conventional approach of causality testing is based on the Granger test (Granger, 1969), which assumes a parametric, linear model for the conditional mean. This specification is simple and appealing as the test is reduced to determining whether the lags of one examined variable enter into the equation of the other, albeit it requires the linearity assumption. In this setup, vector autoregressive residuals are sensitive only to causality in the conditional mean while co-variables may affect the conditional distribution in nonlinear patterns. However, Baek and Brock (1992) noted that the parametric linear Granger causality test has low power against certain nonlinear alternatives or higher moments. As a result, nonparametric causality tests have been proposed in the literature directly emphasizing on prediction without imposing a linear functional form. Hiemstra and Jones (1994) proposed a causality-in-probability test for nonlinear dynamic relationship which is applied to the residuals of vector autoregressions and it is based on the conditional correlation integrals of lead–lag vectors of the variables. This is a modified version of the Baek and Brock test that relaxes the assumption of i.i.d time series and instead allows each series to display weak (or short-term) temporal dependence. It detects the nonlinear causal relationship between variables, including second- or higher-order moment effects, by testing whether the past values influence present and future values. In what follows, the two causality tests are formally described.

3.1 Linear causality

The linear Granger causality test (Granger, 1969) is based on a reduced-form vector autoregression (VAR) model. If $\mathbf{y}_t = \left[y_{1t},\ldots,y_{\ell t}\right]$ is the vector of endogenous variables and ℓ the number of lags, the VAR(ℓ) model is given by

$$\mathbf{y}_t = \sum_{s=1}^{\ell} D_s \mathbf{y}_{t-s} + \varepsilon_t \qquad (1)$$

where D_s is the $\ell \times \ell$ parameter matrix and ε_t the residual vector, for which $E(\varepsilon_t) = \mathbf{0}$ and $E(\varepsilon_t \varepsilon_s') = \begin{Bmatrix} \varepsilon_\varepsilon & t = s \\ \mathbf{0} & t \neq s \end{Bmatrix}$. In case of two stationary time series $\left\{x_t\right\}$ and $\left\{y_t\right\}$ the bivariate VAR model is given by

$$\begin{aligned} x_t &= D(\ell)x_t + F(\ell)y_t + \varepsilon_{x,t} \\ y_t &= G(\ell)x_t + J(\ell)y_t + \varepsilon_{y,t} \end{aligned} \qquad t = 1,2,\ldots,N \qquad (2)$$

where $D(\ell), F(\ell), G(\ell)$ and $J(\ell)$ are lag polynomials with roots outside the unit circle and the error terms are i.i.d. processes with zero mean and constant variance. The test whether y strictly Granger causes x is simply a test of the joint restriction that all coefficients of the lag polynomial $F(\ell)$ are zero, whilst a test of whether x strictly Granger causes y is a test regarding $G(\ell)$. In the unidirectional case the null hypothesis of no Granger causality is rejected if the exclusion restriction is rejected, whereas if both $F(\ell)$ and $G(\ell)$ joint tests for significance are different from zero the series are bi-causally related. However, in order to explore possible effects of cointegration a vector autoregression model in error correction form (Vector Error Correction Model-VECM) is estimated using the methodology developed by Engle and Granger (1987) and expanded by Johansen (1988) and Johansen and Juselius (1990). The bivariate VECM model has the following form

$$\begin{aligned} \Delta x_t &= -p_1\left(\begin{bmatrix}1 & -\lambda\end{bmatrix} \cdot \begin{bmatrix}y_{t-1} & x_{t-1}\end{bmatrix}^T\right) + D(\ell)\Delta x_t + F(\ell)\Delta y_t + \varepsilon_{\Delta x,t} \\ \Delta y_t &= -p_2\left(\begin{bmatrix}1 & -\lambda\end{bmatrix} \cdot \begin{bmatrix}y_{t-1} & x_{t-1}\end{bmatrix}^T\right) + G(\ell)\Delta x_t + J(\ell)\Delta y_t + \varepsilon_{\Delta y,t} \end{aligned} \qquad t = 1,2,\ldots,N \qquad (3)$$

where $\begin{bmatrix}1 & -\lambda\end{bmatrix}$ the cointegration row-vector and λ the cointegration coefficient. Thus, in case of cointegrated time series $\left\{x_t\right\}$ and $\left\{y_t\right\}$ linear Granger causality should be investigated on $F(\ell)$ and $G(\ell)$ via the VECM specification.

3.2 Nonlinear causality

Let $F\left(x_t \middle| \Theta_{t-1}\right)$ denote the conditional probability distribution of x_t given the information set Θ_{t-1}, which consists of an L_x-length lagged vector of x_t, $\mathbf{x}_{t-L_x}^{L_x} \equiv \left(x_{t-L_x}, x_{t-L_x+1}, \ldots, x_{t-1}\right)$ and an L_y-length lagged vector of y_t, $\mathbf{y}_{t-L_y}^{L_y} \equiv \left(y_{t-L_y}, y_{t-L_y+1}, \ldots, y_{t-1}\right)$. Hiemstra and Jones (1994) consider testing for a given pair of lags L_x and L_y the following null hypothesis

$$H_0 : F\left(x_t \middle| \Theta_{t-1}\right) = F\left(x_t \middle| \Theta_{t-1} - \mathbf{y}_{t-L_y}^{L_y}\right) \qquad (4)$$

Denoting the m-length lead vector of $\mathbf{x}_t^m \equiv \left(x_t, x_{t+1}, \ldots, x_{t+m-1}\right)$, for $t \in \mathbf{Z}$, the claim made by Hiemstra and Jones (1994) is that the null hypothesis given in Eq. (4) implies for all $\varepsilon > 0$

$$\begin{aligned} P\left(\left\|\mathbf{x}_t^m - \mathbf{x}_s^m\right\| < \varepsilon \,\middle|\, \left\|\mathbf{x}_{t-L_x}^{l_x} - \mathbf{x}_{s-L_x}^{L_x}\right\| < \varepsilon, \left\|\mathbf{y}_{t-L_y}^{l_y} - \mathbf{y}_{s-L_y}^{L_y}\right\| < \varepsilon\right) \\ = P\left(\left\|\mathbf{x}_t^m - \mathbf{x}_s^m\right\| < \varepsilon \,\middle|\, \left\|\mathbf{x}_{t-L_x}^{l_x} - \mathbf{x}_{s-L_x}^{L_x}\right\| < \varepsilon\right) \end{aligned} \qquad (5)$$

For the time series of realizations $\{x_t\}$ and $\{y_t\}$, $t = 1, \ldots, T$, the nonparametric test consists of choosing a value for ε typically in $[0.5,\ 1.5]$ after unit variance normalization, and testing Eq. (5) by expressing the conditional probabilities in terms of the corresponding ratios of joint probabilities

$$\begin{aligned} C_1\left(m + L_x, L_y, \varepsilon\right) &\equiv P\left(\left\|\mathbf{x}_{t-L_x}^{m+L_x} - \mathbf{x}_{s-L_x}^{m+L_x}\right\| < \varepsilon, \left\|\mathbf{y}_{t-L_y}^{L_y} - \mathbf{y}_{s-L_y}^{L_y}\right\| < \varepsilon\right) \\ C_2\left(L_x, L_y, \varepsilon\right) &\equiv P\left(\left\|\mathbf{x}_{t-L_x}^{L_x} - \mathbf{x}_{s-L_x}^{L_x}\right\| < \varepsilon, \left\|\mathbf{y}_{t-L_y}^{L_y} - \mathbf{y}_{s-L_y}^{L_y}\right\| < \varepsilon\right) \\ C_3\left(m + L_x, \varepsilon\right) &\equiv P\left(\left\|\mathbf{x}_{t-L_x}^{m+L_x} - \mathbf{x}_{s-L_x}^{m+L_x}\right\| < \varepsilon\right) \\ C_4\left(L_x, \varepsilon\right) &\equiv P\left(\left\|\mathbf{x}_{t-L_x}^{L_x} - \mathbf{x}_{s-L_x}^{L_x}\right\| < \varepsilon\right) \end{aligned} \qquad (6)$$

Thus, Eq. (5) can be formulated as

$$\frac{C_1\left(m + L_x, L_y, \varepsilon\right)}{C_2\left(L_x, L_y, \varepsilon\right)} = \frac{C_3\left(m + L_x, \varepsilon\right)}{C_4\left(L_x, \varepsilon\right)} \qquad (7)$$

Using correlation-integral estimators and under the assumptions that $\{x_t\}$ and $\{y_t\}$ are strictly stationary, weakly dependent and satisfy the mixing conditions of Denker and Keller (1983), Hiemstra and Jones (1994) show that

$$\sqrt{n}\left(\frac{C_1\left(m + L_x, L_y, \varepsilon, n\right)}{C_2\left(L_x, L_y, \varepsilon, n\right)} - \frac{C_3\left(m + L_x, \varepsilon, n\right)}{C_4\left(L_x, \varepsilon, n\right)}\right) \sim N\left(0, \sigma^2\left(m, L_x, L_y, \varepsilon\right)\right) \qquad (8)$$

with $\sigma^2\left(m, L_x, L_y, \varepsilon\right)$ as given in their appendix. One-sided critical values are used based on this asymptotic result, rejecting when the observed value of the test statistic in Eq. (8) is too large.

4. STEPWISE MULTIVARIATE FILTERING

A three-step methodology is introduced in order to explore the direction and nature of the dynamic relationships. In the first pre-filtering step, the linear and nonlinear linkages are explored via the application of both the Granger causality test and the modified Baek-Brock test on the raw log-differenced time series of the stock indices. Then, VAR filtering is implemented on the return series and the residuals are examined pairwise by the modified Baek-Brock test. After this step any remaining causality is strictly nonlinear in nature, as the VAR model has already filtered out linear causality of the residuals. Finally, the hypothesis of nonlinear non-causality is investigated after controlling for conditional heteroskedasticity in the data using multivariate GARCH models with various representations. This approach allows the entire variance-covariance structure and the correlation matrix of the stock market interrelationship to be incorporated. The use of the modified Baek-Brock test on filtered data with a multivariate GARCH model enables to determine whether the posited model is sufficient to describe the relationship among the series. If the statistical evidence of nonlinear Granger causality lies in the conditional variances and covariances then it would be strongly reduced when the appropriate multivariate GARCH model is fitted to the raw or linearly VAR filtered data. Many GARCH models can be used for this purpose. However, failure to accept the no-causality null hypothesis may also constitute evidence that the selected multivariate GARCH model was incorrectly specified. This line of analysis is similar to the use of the univariate BDS test on raw data and on GARCH models (Brock et al., 1996; Brooks, 1996; Hsieh, 1989).

Moreover, the correct representation of the conditional covariances in financial markets is guaranteed by the proper parameterization of the univariate conditional variances. In this study, in order to account for the stylized facts of the stock market returns, the asymmetric Glosten-Jagannathan-Runkle (1993) GJR-GARCH(1,1) specification is used for modelling the univariate conditional variances in the conditional correlation representations. Hence, it is properly assumed that the asymmetric behaviour, i.e., skewness of the conditional covariances in the left tails is guaranteed by the GJR-GARCH parameterization of the conditional variances and that the return distributions exhibit high kurtosis due to the presence of fat tails. The multivariate models used for the stepwise filtering are formally described thereafter.

Let $\{y_t\}$ be a vector stochastic return process of dimension $\mathrm{N}\times 1$ and ω a finite vector of parameters. Then $y_t = \mu_t(\omega) + \varepsilon_t$ where $\mu_t(\theta)$ is the conditional mean vector and $\varepsilon_t = H_t^{1/2}(\omega) z_t$ where $H_t^{1/2}(\omega)$ is a $N\times N$ positive definite matrix. Furthermore, the $N\times 1$ random vector z_t have $E(z_t) = 0$ and $Var(z_t) = I_N$ as the first two moments where I_N is the identity matrix. Hence H_t is the conditional variance matrix of y_t.

4.1 VEC and BEKK Models

In the general VEC model, each element of H_t is a linear function of the lagged squared errors and cross-products of errors and lagged values of H_t elements (Bollerslev *et al.*, 1988). The VEC(1, 1) model is defined as

$$h_t = \alpha + \Lambda\eta_{t-1} + \mathrm{M}h_{t-1} \qquad (9)$$

where $h_t = vech(H_t)$, $\eta_t = vech(\varepsilon_t\varepsilon_t{}')$ and vech $(.)$ is the operator that stacks the lower triangular part of a $N\times N$ matrix as a $N(N+1)/2\times 1$ vector. Also, Λ and M are square parameter matrices and α is a parameter vector. The large number of parameters, $N(N+1)(N(N+1)+1)/2$, implies that in practice this model is used only in the bivariate case. To overcome this problem Bollerslev *et al.* (1988) suggest the diagonal VEC (DVEC) model in which the Λ and M matrices are assumed to be diagonal, each element h_{ijt} depending only on its own lag and on the previous value of $\varepsilon_{it}\varepsilon_{jt}$.

As it is difficult to guarantee the positivity of H_t in the VEC representation without imposing strong restrictions on the parameters, Engle and Kroner (1995) propose a new parametrization of H_t that imposes its positivity, namely the Baba-Engle-Kraft-Kroner (BEKK) model. The full BEKK(1, 1, K) model is defined as:

$$H_t = C^{*\prime}C^* + \sum_{k=1}^{K}\Lambda_k^{*\prime}\varepsilon_{t-1}\varepsilon_{t-1}'\Lambda_k^* + \sum_{k=1}^{K}\mathrm{M}_k^{*\prime}H_{t-1}\mathrm{M}_k^* \qquad (10)$$

where C^*, Λ_k^* and M_k^* are $N\times N$ matrices but C^* is upper triangular. The summation limit K determines the generality of the process[2] and the sufficient conditions to identify BEKK models are that $\Lambda_{k,11}^*, \mathrm{M}_{k,11}^*$ and the diagonal elements of C^* are restricted to be positive. To reduce the

[2] The BEKK model is a special case of the VEC model (Engle and Kroner, 1995). To avoid observationally equivalent structures Engle and Kroner (1995) provide sufficient conditions to identify BEKK models with $K = 1$ (Bauwens *et al.*, 2006).

$N(5N+1)/2$ number of parameters in the BEKK(1,1,1) model and consequently to reduce the generality, a diagonal BEKK model can be imposed, i.e. Λ_k^* and M_k^* in (10) are diagonal matrices.

Maximum likelihood estimation is used for VEC and BEKK models. Suppose that the stochastic process has conditional mean, conditional variance matrix and conditional distribution $\mu_t(\omega_0), H_t(\omega_0)$ and $p(y_t \mid \xi_0, I_{t-1})$ respectively, where $\xi_0 = (\omega_0 \eta_0)$ is a r-dimensional parameter vector and η_0 is the vector of the parameters of the innovations distribution z_t , that are assumed i.i.d[3]. The density function is denoted $g(z_t(\omega) \mid \eta)$, where η is a vector of nuisance parameters. The problem to solve is thus to maximize the sample loglikelihood $L_T(\xi) = \sum_{t=1}^{T} \log f(y_t \mid \xi, I_{t-1})$ with $f(y_t \mid \xi, I_{t-1}) = \left|H_t\right|^{-1/2} g\left(H_t^{-1/2}(y_t - \mu_t) \mid \eta\right)$ and the dependence with respect to ω occurs through μ_t and H_t. The term $\left|H_t\right|^{-1/2}$ is the Jacobian that arises in the transformation from the innovations to the observables. The most commonly employed distribution in the literature is the multivariate normal (Harvey *et al.*, 1992; Fiorentini *et al.*, 2003)[4].

4.2 Conditional Correlation Models

These models allow both for individual conditional variances and a conditional correlation matrix between the individual series. Bollerslev (1990) proposes a class of MGARCH models in which the conditional correlations are constant and conditional covariances are proportional to the product of the corresponding conditional standard deviations. This restriction greatly reduces the number of unknown parameters and simplifies the estimation. The CCC model is defined as

$$H_t = G_t R G_t = \left(\rho_{ij}\sqrt{h_{iit} h_{jjt}}\right) \qquad (11)$$

where $G_t = diag\left(h_{11t}^{1/2} \ldots h_{NNt}^{1/2}\right)$. It should be noted that h_{iit} can be defined as any univariate GARCH model, and $R = (\rho_{ij})$ is a symmetric positive definite matrix containing the constant conditional correlations with $\rho_{ii} = 1, \forall i$. The classical CCC model has a GARCH(1, 1) specification for each conditional variance in G_t. In this study the Glosten-Jagannathan-Runkle (1993) GJR-GARCH(1,1) model is applied

[3] The i.i.d. assumption may be replaced by the weaker assumption that is a martingale difference sequence, but this type of assumption does not translate into the likelihood function. The likelihood function for the i.i.d. case can then be viewed as a quasi-likelihood function (Bauwens *et al.*, 2006).

[4] The asymptotic properties of ML and QML estimators in multivariate GARCH models are not yet established, and are difficult to derive from these assumptions. Consistency has been shown by Jeantheau (1998), but asymptotic normality of the QMLE is not established generally. Gourieroux (1997) proves it for a general formulation, while Comte and Lieberman (2003) prove it for the BEKK formulation (Bauwens *et al.*, 2006).

$$h_{ii,t}^2 = \lambda + \beta Y_{t-1}^2 + \gamma h_{ii,t-1}^2 + \delta Y_{t-1}^2 I_{t-1} \qquad (12)$$

where $\lambda \geq 0, \beta \geq 0, \gamma \geq 0, \delta \geq 0$, $I_{t-1} = 1$ when $Y_{t-1} < 0$ and zero otherwise. H_t is positive definite if and only if all the N conditional variances are positive and R is positive definite. The unconditional variances are easily obtained, as in the univariate case, but the unconditional covariances are difficult to calculate because of the nonlinearity in Eq. (11).

The assumption of a constant conditional correlation often seems unrealistic in many empirical applications. Christodoulakis and Satchell (2002), Engle (2002) and Tse and Tsui (2002) propose a generalization of the CCC model by making the conditional correlation matrix time-dependent. They propose a dynamic conditional correlation (DCC) model, with the additional assumption that the time-dependent conditional correlation matrix has to be positive definite $\forall t$. This is guaranteed under simple conditions on the parameters. The DCC model of Christodoulakis and Satchell (2002) uses the Fisher transformation of the correlation coefficient but it is only a bivariate model. The DCC model of Engle (2002) is genuinely multivariate and particularly useful when modelling high-dimensional data samples. The DCC model of Engle (2002) is defined as

$$H_t = G_t R_t G_t \qquad (13)$$

with $R_t = diag\left(w_{11,t}^{-1/2} \ldots w_{NN,t}^{-1/2}\right) W_t diag\left(w_{11,t}^{-1/2} \ldots w_{NN,t}^{-1/2}\right)$. The $N \times N$ symmetric positive definite matrix $W_t = \left(w_{ij,t}\right)$ is given by $W_t = \left(1 - \alpha - \beta\right)\bar{W} + \alpha u_{t-1} u_{t-1}' + \beta W_{t-1}$, with $u_{i,t} = (\varepsilon_{i,t} / \sqrt{h_{ii,t}})$. $\bar{W}$ is the $N \times N$ unconditional variance matrix of u_t, and α and β are non-negative scalar parameters satisfying $\alpha + \beta < 1$. The correlation coefficient in the bivariate case is

$$\rho_{12t} = \frac{\left(1 - \alpha - \beta\right)\bar{w}_{12} + \alpha u_{1,t-1} u_{2,t-1} + \beta w_{12,t-1}}{\sqrt{\left(\left(1 - \alpha - \beta\right)\bar{w}_{11} + \alpha u_{1,t-1}^2 + \beta w_{11,t-1}\right)\left(\left(1 - \alpha - \beta\right)\bar{w}_{22} + \alpha u_{2,t-1}^2 + \beta w_{22,t-1}\right)}} \qquad (14)$$

One drawback of the DCC models is that α, β are scalars, so that all the conditional correlations follow the same dynamics. Nevertheless, it is necessary in order to ensure that R_t is positive definite.

The DCC model can be estimated consistently using a two-step approach. Engle and Sheppard (2001) show that in the case of the Engle (2002) DCC model, the loglikelihood can be written as the sum of a mean and volatility part, depending on a set of unknown parameters ω_1^*, and a correlation part that depends on ω_2^*. Thus, the quasi-loglikelihood function corresponds to the sum of loglikelihood functions of N univariate models as $QL1_T\left(\omega_1^*\right) = -\frac{1}{2}\sum_{t=1}^{T}\sum_{i=1}^{N}\left[\log\left(h_{iit}\right) + \left[\left(y_{it} - \mu_{it}\right)^2 \big/ h_{iit}\right]\right]$. Given ω_1^* and under appropriate regularity conditions, a consistent, but inefficient, estimator of ω_2^* can be obtained by maximizing $QL2_T\left(\omega_2^* \mid \omega_1^*\right) = -\frac{1}{2}\sum_{t=1}^{T}\left(\log\left|R_t\right| + u_t' R_t^{-1} u_t\right)$, where $u_t = G_t^{-1}\left(y_t - \mu_t\right)$ (Bauwens *et al.*, 2006). The sum of the likelihood functions, plus half of the total sum of squared standardized residuals ($\sum_t u_t' u_t \big/ 2$, which is almost equal to $NT\big/2$), is equal to the loglikelihood for BEKK models.

In this study, the asymmetric Glosten-Jagannathan-Runkle (1993) GJR-GARCH(1,1) specification is used for modelling the univariate conditional variances in both CCC and DCC models in order to properly account for the skewness of the return distributions in the left tails as well as for the high kurtosis due to the presence of fat tails.

5. DATA DESCRIPTION AND PRELIMINARY ANALYSIS

The data comprise daily stock index returns of the US, Europe and the BRIC stock markets defined as $r_t = \log\left(P_t\right) - \log\left(P_{t-1}\right)$, where P_t is the closing level on day t. Specifically, the New York Stock Exchange (NYSE) index and the German index DAX30 are considered for the United States and the Euro area respectively, while for the BRICs the Bovespa (Brazil), RTS index (Russia), Bombay Sensex 100 (India) and Shangai SE Composite (China). The indices are denominated relative to United States dollar (USD) to account for the exchange risk under the perspective of the same investor (Chan *et al.*, 2000)[5]. The total sample spans a time period from the introduction of the Euro, i.e., January 5, 1999, to February 28, 2011 (3170 observations)[6]. The investigated time period covers many "extreme" events and different regimes including among other the rise and fall of the tech-market bubble (or "dot-com" bubble), the financial crisis of 2007-2010 and the Eurozone sovereign debt crisis, initiated in early 2010. Specifically, the dot-com bubble involved most of the companies related to the new e-business sector in the mid-1990s. However, there are many interpretations about the specific point in time in which the mounting bubble started. The prevailing belief sets the starting date precisely on the 5th of December 1996, when the former chairman of the Fed, Alan Greenspan, pronounced the famous "irrational exuberance" speech at the Washington D.C.-based American Enterprise Institute. In March 10, 2000 the technology NASDAQ Composite index peaked at 5,048.62 (intra-day peak 5,132.52), more than double its value just a year before, corresponding to the date

[5] The study was also conducted with the stock indices in local currencies in order to investigate the effect of different numeraires. The descriptive statistics and the causality results were not significantly different, albeit some minor differences were observed in skewness and kurtosis.

[6] The Euro currency was introduced (in non-physical form) on 1 January 1999, when the national currencies of the Eurozone countries ceased to exist independently and were locked at fixed rates. Euro values before 1999 usually refer to ECU (European Currency Unit), a basket of EU currencies. Since the first trading day Euro raised to $1.19. However, by the end of 1999 the Euro had dropped to parity with the dollar leading to emergency action from the G7 to support the common currency in 2001.

when the dot-com bubble "burst" (Greenspan, 2007). Moreover, the financial crisis was triggered by a liquidity shortfall in the United States banking system, which resulted in the collapse of large financial institutions, the "bail out" of banks by national governments, turbulence and downturns in stock markets around the world (Krugman, 2009). The crisis began to affect the financial sector in 2007 when HSBC, the world's largest bank, wrote down its holdings of subprime-related mortgage-backed-securities by $10.5 billion, the first major subprime related loss to be reported. On September 15, 2008, the Lehman Brothers Holdings filed for bankruptcy protection following the massive exodus of most of its clients, drastic losses in its stock, and devaluation of its assets by credit rating agencies. The filing marked the largest bankruptcy in U.S. history. Finally, the sovereign debt crisis in early 2010 concerning Eurozone countries such as Greece, Ireland and Portugal is also investigated. It led to a crisis of confidence as well as the widening of bond yield spreads and risk insurance on credit default swaps between these countries and other Eurozone members. At the beginning of 2010, a €500 million government bond auction in Portugal raised only €300 million, increasing the cost of insuring against a Portuguese debt default (Blackstone *et al.*, 2010). The failed Portuguese bond auction further intensified the fear that the emerging sovereign debt issues could become a global contagion. These fears led to a weakening of the Euro and a widespread global stock and commodity sell off in February 2010 and the following months. Moreover, Greece was the focal point of the crisis through mid-March 2010 and April. Greek government searched for a potential bailout plan – which was eventually decided by Eurozone member states - in case it failed to raise the necessary money to fill its budget gap through the credit markets. The bailout plan for Greece by the EU and IMF failed to reassure investors, thus leading to an agreement of an unprecedented defence package of 750,000€ by the European Union and the IMF, in order to prevent the relentless speculative attacks on the common currency and eventually restore stability. The crisis intensified towards the end of 2009 when there was an abrupt increase in the spreads due to the downgrading of Greece's credit rating by all three major international credit agencies (Fitch, Moody's and S&P).

The robustness of the results is examined in several sub-periods. The financial crisis is considered as a major breakpoint for the identification of the sub-periods, hence setting a platform for departure for causality tests. On *February 22, 2007* the HSBC, the world's largest bank of 2008, wrote down its holdings of mortgage-backed-securities by $10.5 billion. This was the first major subprime related loss to be reported, thus the aforementioned date is used as the crisis breakpoint[7]. Overall, the examined sub-periods are the following: P_1: January 5, 1999 to February 21, 2007 (2122

[7] In addition to the economic rationale the breakpoint selection is statistically tested via the application on the stock return series of Chow's test (Chow, 1960) for known (imposed) breaks and the cumulative sum (CUSUM) test (Brown *et al.*, 1975) for unknown points. The selected breakpoint has also been verified with the Bai and Perron (2003) and Zivot and Andrews (1992) tests.

observations) and P_2: February 22, 2007 to February 28, 2011 (1048 observations). In addition, the entire sample period P_{Total}: January 5, 1999 to February 28, 2011 (3170 observations) is comparatively investigated.

The descriptive statistics for all time series are presented in Table 1. The Jarque-Bera multiplier for all stock markets in all periods is statistically significant, thereby indicating that the return distributions are not normal. They also exhibit zero mean-reversal and low variance. In general, kurtosis for returns in all periods - with the exception of NYSE and DAX in P_1 - is larger than normal which implies the presence of fat tails, extreme observations and possibly volatility clustering. As indicated by skewness, the stock index returns have a longer left tail, while NYSE and DAX before the crisis (P_1) appear to be close to symmetric. Based on the Ljung-Box Q-statistic, the hypothesis that all correlation coefficients of the returns up to 12 are jointly zero is not rejected in the majority of cases, especially for the BRIC economies. Therefore, it can be inferred that the return series present nonlinear dependence due possibly to clustering effects or conditional heteroscedasticity, a fact that is further substantiated by the results of the ARCH LM-statistic. The differences between the pre- and post-crisis periods P_1 and P_2 are quite evident in Table 1 where a significant increase in the standard deviation can be observed in P_2 for all returns as well as increased fat-tailedness reflected in the higher kurtosis. Additionally, P_2 witnessed many occasional negative spikes as it can be inferred from the skewness. Table 1 also reports the contemporaneous correlation matrix for all periods. Significant sample cross-correlations are noted for NYSE, DAX and BOVESPA indicating a high interrelationship among those markets, while in general all series are positively correlated in both periods. Low correlation or uncorrelatedness is also observed mostly for China. More importantly, after the crisis emerged (P_2) the cross-correlations among all markets are significantly increased both between the US or Eurozone and the BRICs, as well as among the BRIC economies. However, these results should be cautiously interpreted as linear correlations cannot fully capture the dynamic linkages in a reliable way. Consequently, a long-term causality analysis is necessary.

Nonstationarity is tested with the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests, both of which are applied to the log-levels and returns (Table 2). The lag length is selected using the Schwartz Bayesian Information Criterion (SIC), while for the PP test the bandwidth is automatically selected using Newey and West (1994) method with Bartlett kernel. All variables appear to be nonstationary in log-levels and stationary in log-returns based on the reported *p*-values. In particular, the ADF and PP tests indicate that the null of a unit root cannot be rejected at 1% for the log-levels in all periods, regardless of whether a constant and linear trend or only a constant is included in the deterministic component. Furthermore, both tests show that the log-returns are stationary as the null can be soundly rejected for all stock indices and periods. The combined results from the unit root tests suggest that all investigated log-levels appear to be $I(1)$ processes. Based on these results and in order to identify the correct model specification for the investigation of linear and nonlinear causality (i.e., VAR or VECM), the trace and maximum eigenvalue statistics were further applied to the log-prices series to explore possible effects of cointegration (Johansen, 1988; Johansen and Juselius, 1990). For all pairs the Johansen tests did not identified any cointegrating vectors and the null of no cointegration was not rejected (Table 3).

[Please insert Tables 1, 2 and 3 here]

6. EMPIRICAL RESULTS

The nature and direction of causalities is explored initially via the application of both the Granger causality test and the modified Baek-Brock test on the raw stock index returns. Moreover, as described in Section 4, vector autoregressive filtering is implemented on the return series and the residuals are examined pairwise by the modified Baek-Brock test. Any remaining causality is strictly nonlinear in nature, as the autoregressive filter has already "whitened" out the linear causality of the residuals. Finally, nonlinear non-causality is investigated after controlling for conditional heteroskedasticity through multivariate GARCH filtering.

Based on the cointegration results in Section 5, linear and nonlinear causality is investigated with a VAR model representation. The results from the Schwartz Information Criterion criterion, taking into consideration many lag specifications for each pairwise VAR modelling, indicate in most of the cases four lags for the stock index return series in all periods[8]. For the modified Baek-Brock nonlinear causality test in what follows, the common lag lengths used are $\ell_X = \ell_Y = 1$. The test is applied on the VAR residuals derived from the pairwise linear causality testing and the distance measure is set to $\varepsilon = 1.5$, as suggested by Hiemstra and Jones (1994)[9].

Moreover, in order to capture the information transmission mechanism between the US, the Eurozone and BRIC equity markets and to reduce the effect of non-synchronous trading, the chronological order of the operating time of the equity markets must be taken into account and specified time differentials should be used appropriately. The trading hours of the stock exchanges

[8] Each bivariate vector autoregression (VAR) examined for the causality analysis, contained up to twelve lags. The Schwartz Bayesian Information criterion (SIC) concluded in most cases on four lags for the US, Eurozone and BRIC stock index return series in the investigated periods. Overall, no significant differentiation in the causality results is observed in assuming other than the selected lags for the return time series.

[9] In the estimation $\varepsilon = 0.5$ and $\varepsilon = 1$ were also considered, with no qualitative difference in the results. In addition, evidence from the second and third common lag lengths did not significantly modified the nonlinear causality results.

are not perfectly synchronized, though there are several overlapping hours in each trading day for some markets. It is well known that trading day starts in the Asia-Pacific region and the order of the opening of the five equity markets is: China, India, Russia, EU (Germany), Brazil and the last market to trade is US. Table 4 presents the trading hours sequence with the use of Greenwich time as well as US Eastern time with a chronological order from day $t-1$ to day t. The US stock market shares almost all of its trading hours with the Brazilian stock market. Also, the Chinese, Indian, and Russian markets have overlapping trading hours and in general their trading activity can be considered to a large extent concurrent. However, the US returns are known to traders before the opening of the stock markets in China, India, and Russia. Because of these non-concurrent trading hours a hypothesis testing problem arises; if the US and the Asia-Pacific region – that share almost entirely non-overlapping trading hours - were tested concurrently at time t (corresponding to a weekday in the time series calendar data), then the Granger causality tests would most probably presume the biased unidirectional causalities, as news coming from US at time $t-1$ affects consistently the other aforementioned markets at time t. Similarly, the unidirectional causality from the Asian markets at time t to the US of the same calendar day t is also pre-assumed and obvious. Thus, in order to remove the testing bias due to the information flows, "align" the time series calendar dates and eventually avoid inaccurate conclusions, the bi-directional null hypothesis for the linear and nonlinear causality will be tested in the one direction at time $t-1$ for the US market, while for the other direction on the concurrent series at time t. It is noted that the linear and nonlinear causality exercise performed in this study aims at investigating the spillover, second-moment effects (if any) that drive the market interdependencies and not the natural one-period lagged flows of news among the non-overlapping markets. For example, on the basis of the time series calendar daily data used, in case of China (the same applies to India and Russia) it will be tested that H_0: China_t does not Granger cause US_{t-1}, while for the other direction H_0: US_t does not Granger cause China_t.[10] In general, the differences in closing times could potentially cause sequential price responses to common information that could be mistaken for causal linkages. Intraday data could be used to disassociate these sequential responses from causal transmissions within a particular day. Regrettably these data are not available for the BRIC markets.

[10] In both cases H_1 assumes an obvious dependence and thus is not considered. Additionally, in terms of the time index and consequently the calendar data order used in the causality investigation, it is equivalent to test the hypotheses H_0: China_{t+1} does not Granger cause US_t and H_0: US_{t+1} does not Granger cause China_{t+1}. The causality exercise was also conducted in a lower frequency (weekly) and the results analyzed in the next sections were found similar.

Overall, the results are reported in the corresponding columns of Table 5. The simplifying notation " ** " is used to indicate that the corresponding *p*-value of the causality test is smaller than 1% and " * " that the corresponding *p*-value of a test is in the range 1-5%; Directional causalities will be denoted in text by the functional representation → or ↔ for unidirectional and bidirectional linkage respectively.

[Please insert Table 4 here]

6.1 Linear and nonlinear causality detection on raw returns

The linear causality results on raw returns reveal the strong feedback relationships US↔Russia, US↔India and EU↔Brazil at the 1% significance level for all periods. In addition, the strong unidirectional linkages of US→Brazil and EU→China are observed in all periods. Interestingly, these economies appear to lack any causal relationship in the other direction. Moreover, US and China present a strong bidirectional linkage in P_2 and P_{Total}. The fact that it vanishes in the pre-crisis period P_1 suggests that it was generated after the burst of the financial crisis, which predominately impacted the US stock market. Finally, EU appears to linearly Granger cause Russia and India in all periods at the 1% significance level, yet the opposite relationship is only observed at the 5% level in P_2 and not detected at all in P_1. Thus, in the period before the crisis neither Russia nor India Granger caused the German financial market.

Table 5 also reports the results of the nonlinear causality on the raw returns. Interestingly, before VAR filtering, persistent nonlinear bidirectional interdependencies are detected in all periods for all countries except China. Specifically, EU appears to weakly cause China only in P_2, while US causes China in P_2 and P_{Total} at the 1% significance level. In addition, the strong unidirectional linkage China→US is also revealed in P_{Total}.

6.2 Nonlinear causality testing on VAR-filtered residuals

The results on raw series suggest that there are significant and persistent linear and nonlinear causal linkages between US, EU and the BRICs. Next, the modified Baek-Brock test is reapplied on filtered VAR-residuals to ensure that any causality found is strictly nonlinear in nature. The application of the nonlinear causality test points towards the preservation of the results reported for the "non-whitened" raw returns. Interestingly, the comparison of the summary results in Table 5 reveals identically significant nonlinear relationships with few exceptions. In particular, the causal relationship EU→India in P_1 has now vanished, while the unidirectional linkages US→Brazil and US→China in P_2 have weakened and are now detected at the 5% significance level. The nature and source of the detected nonlinearities may also imply a temporary, or long-term, causal relationship among the investigated financial markets. Indicatively, second-moment effects might induce nonlinear causality especially in the time period after the financial crisis. Given the status of the US economy, an innovation in the US stock market may seriously affect the extent of dependency and volatility spillovers across BRICs' markets. The volatility transmission mechanism can be investigated after controlling for conditional heteroskedasticity using a multivariate representation, so that entire variance-covariance structure of the market interrelationship is incorporated.

6.3 Residual nonlinear interdependencies after multivariate GARCH filtering

After GARCH-BEKK filtering, only in a few cases the nonlinear linkages are removed. Specifically, the EU→China relationship in P_2 is purged as well as the US→Brazil in P_1 and P_2 and the Brazil→US, yet only in P_1. In addition, the unidirectional linkage of Russia→EU is purged in P_1 and P_2 and weakened in P_{Total}. The fact that all other remaining nonlinear interdependencies after VAR filtering persist even after GARCH-BEKK filtering, suggests that volatility effects under this particular variance-covariance representation are not the ones inducing nonlinear causality.

Instead, most of the nonlinear linkages after CCC-GARCH and DCC-GARCH filtering have vanished. Of course this does not apply to all examined pairs, but overall the "whitened" residuals after filtering heteroscedasticity with these models present different causal relationships compared to the GARCH-BEKK[11]. Additionally, the major differences with the VAR-filtered residuals indicate that the nonlinear causality was largely due to simple volatility effects that were not captured by the BEKK formulation. Indeed, the use of the asymmetric GJR-GARCH specification for modelling the univariate conditional variances in both CCC and DCC models in order to account for the skewness and high kurtosis of the return distributions, provided with better results[12]. In particular, for China all linkages have disappeared vis-à-vis the US and EU, while only a few still remain in the post-crisis period P_2 (and P_{Total}) for the pair US-Brazil and for EU and Brazil, Russia and India. Moreover, the remaining relationships are considerably weakened in terms of statistical significance.

However, this is not indicative of a general conclusion. Interestingly, significant nonlinear interdependencies remain after the conditional correlation filtering, revealing that second-moment effects and volatility spillovers are probably not the only ones inducing nonlinear causality. In case of the US-Russia and US-India pairs, strong feedback relationships remain in all periods except for P_2. Consequently, the dependencies in the post-crisis period were probably due to second-moment effects, that is why they were captured and removed by the GARCH filtering. On the contrary, it

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[11] A GARCH-BEKK specification with Student-*t* error structure has also been tried, but the nonlinear causality results were not modified.

[12] The use of the classical Bollerslev (1986) GARCH(1,1) specification for modelling the univariate conditional variance in CCC and DCC proved to be less successful in terms of remaining causalities, especially for EU and Brazil, Russia and India.

seems that the causal linkages in the pre-crisis period P_1 are not attributed to a volatility transmission mechanism, as they were nor purged in P_1 but most importantly remain also in P_{Total}. Thus, the US-Russia and US-India causality interdependencies were not eroded due to volatility clustering during the pre-crisis period (Bekaert and Harvey, 2003). Moreover, they are not statistically weakened at all after the multivariate GARCH filtering. One possible explanation could be that third- or higher-moment causality may be a significant factor of the remaining interdependence. Also, the remaining causalities could be due to tail dependency that exists even if volatility clustering is accounted for. These results could also lead to policy implications considering portfolio diversification in these financial markets.

[Please insert Table 5 here]

7. ECONOMIC AND POLICY IMPLICATIONS

An interesting conclusion with respect to the globalization of the stock markets emerged from this study, in that all markets considered here have become more internationally integrated after the US financial crisis and the consequent Eurozone sovereign debt crisis. Moreover, it is evident from the results that mean and volatility spillover effects exist not only from the US market to the developed equity markets of Europe and Asia as shown in previous studies, but they also exist between the US the BRIC economies. Another finding is that some differences exist between the persistence and strength of the causal linkages in the pre- and post-crisis period. In view of the fact that BRICs pertain strong linkages with the global economy through trade and financial markets, a contagion effect was further substantiated due the transmission of the US subprime crisis to the BRIC equity markets. For instance, the post-crisis period exhibits highly significant feedback spillovers between the US market and the BRICs, with the exception of China which is always Granger caused by US and the EU. Results from both periods show that India and Russian equity returns were highly affected by the movements in the US market. For Russia in particular, a clear evidence of contagion is established after the Lehman brother's bankruptcy.

The leading role of the US market in the world financial system is visible throughout all causality tests and in all time periods, a fact that is consistent with earlier findings by Eun and Shim (1989). On the other hand, the Chinese market has relatively little influence on the stock price movements in the US and EU, particularly once linear effects have been removed through VAR-filtering. This finding provides a relative support to the view that China plays a passive role in transmitting information to other stock markets.

Moreover, the volatility of US, Chinese, and Indian equity markets may be interrelated through investment, trade and macroeconomic fundamentals, so that news about the US economic conditions most likely have implications for the Chinese and Indian economies and financial markets. However, the trade linkages between the pairs US-Russia and US-Brazil are rather small. Nevertheless, their stock markets may be linked through the impact of world oil and energy demand, which most likely affects the Russian and to some extent the Brazilian economy. In general, the US, EU and the BRIC economies are also related through changes in currency markets which affect their relative competitiveness. In the financial sector foreign exchange volatility may also induce global portfolio managers to dynamically modify their investment positions among the six markets[13]. One other reason of the remaining causalities could be that speculative movements driven by trader fads may be transmitted to and from the US, EU and the BRIC stock markets. Thus, speculative and noise trading may also lead to contagion effects across the investigated markets.

Finally, beyond the contagious effects of the US crisis on the BRIC equity markets, the present study explored the so called "decoupling" phenomenon. It seems that some evidence in support of the decoupling view was found based on the causality results. Specifically, the assumption that the emerging markets can be major drivers of world growth is partially validated by the detected feedback linkages. However, decoupling would have been plausible, especially after the financial crisis period, only if strong unidirectional links were detected from the BRICs to the US market and not of the opposite direction as well.

8. CONCLUSIONS

The present study contributes to the literature on spillovers among the global financial markets by focusing on the high-growth emerging equity markets of Brazil, Russia, India, and China - the so-called BRIC economies - that have hitherto received little attention. It explores the linkages among the developed US and Eurozone equity markets and the BRICs, and investigates the transmission of the US subprime crisis to the fastest growing economies of the world. The aim of the study is to test for the existence of both linear and nonlinear causal relationships among the examined financial markets, within the time period from the introduction of Euro until the financial crisis of 2007-2010 and the consequent EU debt crisis.

Several interesting conclusions have emerged from this study. In particular, it was shown that almost all markets have become more internationally integrated after the US financial crisis and the consequent Eurozone sovereign debt crisis. Whilst the linear causal relationships detected on the

[13] Although in this study the stock indices were denominated relative the USD to account for the exchange risk under the perspective of the same investor (Chan *et al.*, 2000), the causality results in local currencies were not found to be statistically different.

stock returns have disappeared after proper filtering, nonlinear causal linkages in some cases emerged and more importantly persisted even after multivariate GARCH filtering both in the pre- and post-financial crisis period. Contagion was further substantiated due the transmission of the US subprime crisis to the BRIC markets, as well as via trade interrelationships mostly during the post-crisis period. In addition, the leading role of the US market is shown throughout all causality tests and in all time periods, whereas the Chinese market has relatively little influence on the stock price movements in the US and EU, particularly once linear effects have been removed. US, Chinese, and Indian equity markets may be interrelated through investment, trade and macroeconomic fundamentals, while the US, Russian and Brazilian stock markets may be linked through the energy demand. Finally, beyond the contagious effects of the US crisis on the BRIC equity markets, the "decoupling" phenomenon was also investigated. The assumption that the BRICs are major drivers of world growth was confirmed by the detected feedback linkages. However, decoupling was not observed as this would entail unilateral strong links from the BRICs to the US market and not of the opposite direction as well, especially after the financial crisis period.

An interesting topic for future research is the nature and source of the nonlinear causal interdependencies. It was conjectured that volatility effects might partly induce nonlinear causality. The fitted multivariate conditional correlation GARCH models account for a large part of the nonlinearity, albeit not in all cases. Alternatively, other parametrized GARCH models or structural models may be employed, the latter of which would incorporate economic factors and macro-fundamentals driving the interdependence of emerging stock markets. Moreover, the probability that stock returns may exhibit third- or higher-moments should not be excluded. Also, the remaining causalities could be due to tail dependency that exists even if volatility clustering is accounted for. These factors may explain why GARCH filtering does not capture all the nonlinearity in stock returns.

The empirical findings could have many implications for the efficiency of the BRIC markets. For instance, these results may be useful in future research to quantify the process of financial integration of these markets as well as influence their predictability. The detected interdependencies among US, EU and the BRICs could also have important implications for financial market regulations, hedging and trading strategies. The fact that there are long-term links between these markets implies that excess risk-adjusted returns exist. Also the presence of dynamic linear and nonlinear relationships may be used to achieve gains from international portfolio diversification and to reduce systematic market risk.

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TABLE 1: DESCRIPTIVE STATISTICS

Statistic	NYSE			DAX			BOVESPA			RTS			BSE			SSE		
	P_{Total}	P_1	P_2	P_{Total}	P_1	P_2	P_{Total}	P_1	P_2	P_{Total}	P_1	P_2	P_{Total}	P_1	P_2	P_{Total}	P_1	P_2
Mean	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.001	0.001	0.001	0.002	0.000	0.001	0.001	0.000	0.000	0.000	0.000
Std. dev.	0.013	0.010	0.018	0.017	0.015	0.020	0.025	0.024	0.029	0.024	0.023	0.027	0.019	0.017	0.023	0.016	0.014	0.021
Variance	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.001	0.001	0.001	0.001	0.001	0.000	0.000	0.001	0.000	0.000	0.000
Skewness	-0.270	0.007	-0.288	0.008	-0.099	0.107	-0.181	-0.070	-0.305	-0.319	-0.280	-0.333	-0.191	-0.521	0.111	-0.056	0.537	-0.383
Kurtosis	9.761	2.674	6.645	4.915	2.357	5.783	5.960	4.170	7.171	8.124	5.049	11.022	6.302	4.154	6.359	4.283	5.287	2.352
JB test	12579.0*	627.8*	1920.7*	3178.9*	491.0*	1445.4*	4691.7*	1529.8*	2236.8*	8739.1*	2268.3*	5268.6*	5244.6*	1612.2*	1747.7*	2414.8*	2559.0*	263.6*
Q(12)	36.67*	15.65	29.24*	30.76*	23.92*	22.35	44.32*	51.45*	23.49*	56.56*	28.71*	59.45*	72.94*	47.26*	33.34*	28.91*	22.93*	12.13
ARCH -LM(5)	236.72*	59.91*	79.87*	112.42*	81.46*	34.12*	159.19*	53.73*	99.31*	80.27*	37.57*	33.35*	47.15*	81.94*	7.86*	34.52*	21.21*	7.48*

Correlation matrix

	P_{Total}						P_1						P_2					
	NYSE	**DAX**	**BOVESPA**	**RTS**	**BSE**	**SSE**	**NYSE**	**DAX**	**BOVESPA**	**RTS**	**BSE**	**SSE**	**NYSE**	**DAX**	**BOVESPA**	**RTS**	**BSE**	**SSE**
NYSE	-						-						-					
DAX	*0.596*						*0.566*						*0.637*					
BOVESPA	*0.581*	*0.515*					*0.435*	*0.364*					*0.740*	*0.712*				
RTS	*0.273*	*0.386*	*0.345*				*0.184*	*0.238*	*0.214*				*0.370*	*0.584*	*0.534*			
BSE	*0.228*	*0.294*	*0.252*	*0.312*			*0.072*	*0.134*	*0.118*	*0.206*			*0.358*	*0.476*	*0.420*	*0.448*		
SSE	*0.054*	*0.095*	*0.106*	*0.104*	*0.176*	-	*-0.004*	*0.002*	*0.010*	*-0.006*	*0.043*	-	*0.097*	*0.191*	*0.215*	*0.232*	*0.308*	-

Notation: (*) denotes significance at 5% confidence level. The periods are P_1: 01/05/1999-02/21/2007, P_2: 02/22/2007-02/28/2011 and P_{Total}: 01/05/1999-02/28/2011

TABLE 2: UNIT ROOT TESTS

Periods		PTotal				P1				P2			
Variables		ADF		PP		ADF		PP		ADF		PP	
		ADF_c	ADF_τ	PP_c	PP_τ	ADF_c	ADF_τ	PP_c	PP_τ	ADF_c	ADF_τ	PP_c	PP_τ
NYSE	P_t	0.53	0.71	0.53	0.72	0.95	0.95	0.97	0.97	0.60	0.96	0.62	0.96
	r_t	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*
DAX	P_t	0.79	0.67	0.78	0.68	0.96	0.99	0.97	0.99	0.62	0.92	0.63	0.92
	r_t	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*
BOVESPA	P_t	0.92	0.57	0.93	0.58	0.99	0.98	0.99	0.99	0.52	0.77	0.53	0.78
	r_t	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*
RTS	P_t	0.85	0.76	0.84	0.75	0.99	0.99	0.99	0.98	0.72	0.97	0.74	0.98
	r_t	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*
BSE	P_t	0.82	0.54	0.82	0.55	0.99	0.99	0.99	0.99	0.54	0.84	0.55	0.84
	r_t	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*
SSE	P_t	0.71	0.82	0.71	0.81	0.99	0.99	0.99	0.99	0.60	0.72	0.59	0.72
	r_t	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*

Notation: Price variables are in logarithms and reported numbers for the augmented Dickey–Fuller (ADF) and Phillips-Perron (PP) test are p-values (both are one-sided tests of the null hypothesis that the variable has a unit root). The index c indicates that the test allows for a constant, while τ for a constant and a linear trend. The number of lags for the ADF was selected using the Schwarz information criterion. The lag truncation for the PP test was selected using Newey and West (1994) automatic selection with Bartlett kernel. (*) denotes significance at 1% confidence level. The periods are P_1: 01/05/1999-02/21/2007, P_2: 02/22/2007-02/28/2011 and P_{Total}: 01/05/1999-02/28/2011

TABLE 3: COINTEGRATION TESTS

Pair		Trace statistic						Maximum Eigenvalue statistic					
X	Y	PTotal		P1		P2		PTotal		P1		P2	
		$r=0$	$r\leq 1$	$r=0$	$r\leq 1$	$r=0$	$r\leq 1$	$r=0$	$r\leq 1$	$r=0$	$r\leq 1$	$r=0$	$r\leq 1$
NYSE	**BOVESPA**	0.95	0.91	0.11	0.27	0.48	0.22	0.92	0.91	0.11	0.27	0.57	0.22
	RTS	0.70	0.47	0.50	0.10	0.64	0.28	0.68	0.48	0.81	0.10	0.71	0.28
	BSE	0.87	0.43	0.20	0.22	0.58	0.24	0.88	0.43	0.24	0.22	0.67	0.24
	SSE	0.59	0.23	0.11	0.52	0.34	0.28	0.68	0.24	0.11	0.52	0.36	0.28
DAX	**BOVESPA**	0.88	0.76	0.27	0.56	0.80	0.20	0.84	0.76	0.22	0.56	0.92	0.20
	RTS	0.56	0.32	0.49	0.28	0.17	0.28	0.58	0.32	0.53	0.28	0.17	0.28
	BSE	0.42	0.35	0.26	0.86	0.74	0.18	0.42	0.35	0.19	0.86	0.88	0.18
	SSE	0.41	0.47	0.11	0.23	0.36	0.16	0.37	0.47	0.11	0.23	0.47	0.16

Notation: Reported numbers for the trace and max. eigenvalue statistics are the MacKinnon-Haug-Michelis (1999) p-values.

TABLE 4: TRADING HOURS SEQUENCE OF MARKETS (CALENDAR DATE)

Time zone	MARKET					
	USA	**Brazil**	**China**	**India**	**Russia**	**EU (DAX)**
GMT (Greenwich time)	14:30-21:00$_{(t-1)}$	15:00-22:00$_{(t-1)}$	1:30-3:30$_{(t)}$ & 5:00-7:30$_{(t)}$	4:00-11:00$_{(t)}$	7:00-16:00$_{(t)}$	9:00-17:30$_{(t)}$
USA (Eastern time)	9:30-16:00$_{(t-1)}$	10:00-17:00$_{(t-1)}$	19:30-21:30$_{(t-1)}$ & 23:00$_{(t-1)}$ -1:30$_{(t)}$	23:00$_{(t-1)}$ - 6:00$_{(t)}$	2:15$_{(t)}$ -11:05$_{(t)}$	4:15$_{(t)}$ -12:35$_{(t)}$

Notation: The trading hours sequence is presented with the use of Greenwich as well as US Eastern time. The time index notation denotes the chronological order from calendar day *(t-1)* to day *(t)*. In case of China the market involves an intraday intermission of one and a half hours.

TABLE 5: CAUSALITY RESULTS

Pair		Linear Causality						Nonlinear Causality																													
		Raw data						Raw data						VAR						GARCH-BEKK						CCC-GARCH						DCC-GARCH					
X	Y	X→Y			Y→X			X→Y			Y→X			X→Y			Y→X			X→Y			Y→X			X→Y			Y→X			X→Y			Y→X		
		P_{Total}	P_1	P_2	P_{Total}	P_1	P_2	P_{Total}	P_1	P_2	P_{Total}	P_1	P_2	P_{Total}	P_1	P_2	P_{Total}	P_1	P_2	P_{Total}	P_1	P_2	P_{Total}	P_1	P_2	P_{Total}	P_1	P_2	P_{Total}	P_1	P_2	P_{Total}	P_1	P_2	P_{Total}	P_1	P_2
USA	Brazil	**	*	**				**	**	**	**	**	**	**	**	*	**	**	**	**			**		**				*		*				*		*
"	Russia	**	**	**	**	**	**	**	**	**	**	**	**	**	**	**	**	**	**	**	**	**	**	**	**	**	**		**	**	**	**	**		**	**	**
"	India	**	**	**	**	*	**	**	**	**	**	**	**	**	**	**	**	**	**	**	**	**	**	**	**	**	**		**	*	**	**	**		**	*	**
"	China	**		**	**		**	**		**	**			**		*	**			**		*	**														
EU	Brazil	**	**	**	**	**	**	**	**	**	**	**	**	**	**	**	**	**	**	**	**	**	**	**	**	*		*				*		*			
"	Russia	**	*	**	**		*	**	*	**	**	*	**	**	*	**	**	*	**	**	*	*	*			*		*				*					
"	India	**	**	**	**		*	**	*	**	**	*	**	**		**	**	*	**	**		**	**	*	**				*			*			*		
"	China	**	**	**						*						*																					

Notation:

X→Y: r_x does not Granger cause r_y. Statistical significance represents *5% (*)* and *1% (**)*. The stock indices for each country are USA: New York Stock Exchange (NYSE); Eurozone (Germany): DAX30; Brazil: Bovespa; Russia: RTS index; India: Bombay Sensex 100; China: Shangai SE Composite. The indices are denominated relative to United States dollar (USD).

The periods are P_1: 01/05/1999-02/21/2007, P_2: 02/22/2007-02/28/2011 and P_{Total}: 01/05/1999-02/28/2011. The synchronization issues for the correct testing of the null hypothesis in both directions are analyzed in Section 6.

For all pairs the Johansen tests did not identified any cointegrating vectors and the null of no cointegration was not rejected (Table 3). Thus, linear and nonlinear causality are investigated with a VAR representation. The results from the SIC criterion, taking into consideration many lag specifications for the bivariate VAR modelling, indicate in the majority of cases four lags for the return series in all periods.

For the nonlinear causality test the common lag lengths used are $\ell_X = \ell_Y = 1$. The nonlinear test is applied on the VAR residuals derived from the pairwise linear causality testing and the distance measure is set to $\varepsilon = 1.5$, as suggested by Hiemstra and Jones (1994). To account for the stylized facts of the stock market returns, in CCC and DCC representations the asymmetric Glosten-Jagannathan-Runkle (1993) GJR-GARCH(1,1) specification is used to model the univariate conditional variances.