Morales, Lucía; Gassie, Esmeralda

Conference Paper

Structural breaks and financial volatility: Lessons from BRIC countries

IAMO Forum 2011, No. 13

Provided in cooperation with:
Leibniz Institute of Agricultural Development in Central and Eastern Europe (IAMO)

Structural breaks and financial volatility: lessons from BRIC countries

Authors:
Lucía Morales, Dublin Institute of Technology, Dublin[1]*
Esmeralda Gassie, University of Limerick[2]

Last Update: 19th May, 2011

Abstract

Despite the fact that there is a substantial literature on the analysis of volatility spillovers between stock returns and domestic exchange rates, surprisingly, little empirical research has examined volatility spillovers between oil prices and emerging economies, where a clear gap of research have been found regarding to the BRIC financial markets and the effects of the 2007-2009 World economy crisis. This lack of research might appear as surprising given that energy markets are of particular interest as they are considered a fundamental reference for economic recovery and growth. Therefore, this work aims to address this gap on the literature by looking at the BRIC financial markets and their co-movements with regard to some energy markets (oil, natural gas and electricity) and also to the international pressures that may arise from fluctuations originated in the US stock markets. This research major findings show compelling evidence highlighting the weak integration levels that exist among the Chinese financial markets, energy markets and the US stock market. On the other hand, the Brazilian, Indian and Russian markets are found to be more sensitive to international shocks arisen from US markets and also to energy markets instability, especially with regard to oil market uncertainty.

Keywords: BRIC, Energy Markets, GARCH, T-GARCH modeling, Volatility.

JEL Codes: F, G

[1]* Lucía Morales: lucia.morales@dit.ie(corresponding author); Department of Accounting and Finance, Business School, Dublin Institute of Technology. Ireland.
[2] Esmeralda Gassie: esmeralda.gassie@ul.ie; Department of Economics, Kemmy Business School, University of Limerick. Ireland.

Introduction

While Europe is in the midst of rigorous economic and fiscal policy making, the USA is slowly achieving to maintain a calm investment climate. Meanwhile, the newly emerging pillars of the world economy, i.e. Brazil, Russia, India and China are 'allowing' some favors to the developed economies. China has decided to appreciate its Renmibi after being criticized for favoring its exports for the last five years. The latter have increased by half for the first semester of 2010. The fiscal policy is not affected by the recent events as public investments, particularly in construction, can reach up to ten times a province's GDP (in the case of the Hubei province). The newly published OECD report on Global Development states that emerging economies will count for nearly two thirds of the world's GDP by 2030. Similar growth levels were reached by other countries which were later denominated Asian and Celtic Tigers. The various crises these countries experienced first and foremost evidenced their financial fragilities. The evolution of the balance of payments is crucial when choosing a growth path.

The BRIC are not in hurry to open their economies, some having suffered from financial liberalization, some trying to prevent as much as possible similar crises. In any case, these emerging juggernauts draw their own conclusions from the past and current crises. Their policy actions might not always coincide with the international tempo dictated mainly by developed countries. The Russian president has certainly announced his will to reform the Bretton Woods institutions. His motivation is solely a protection towards Russia's trading partners more so than reforming Russian financial institutions. The same for China as the government has decided not to be so dependent on exports and develop the domestic market. This article will review the financial characteristics of these countries in the perspective of prevention of crisis contagion. The question is what specificities allow these countries to better resist the financial and economic hurricane that hit the rest of the developed countries so hard. The lessons, if any, to be drawn from countries seemingly instable and under developed, could lead to reflect and revaluate the financial measures currently being taken in the developed countries.

Volatility of financial assets has been extensively studied for the last twenty years. More particularly, how the reaction to structural breaks undermines volatility persistence over time. This article will precisely measure volatility of stock returns in Brazil, Russia, India and China. The purpose is to evaluate the reaction of financial markets in those countries when instability intervenes through financial crises. Little empirical evidence exists on the matter, even though analysts seem to agree on the emergence of those countries as future economic and financial world level powers.

The article is divided in three sections. Standard estimates and more recent models of volatility will be reviewed in the first section in order to come up with the methodology that is best adapted to the issue of volatility persistence over time. The models retained will be tested with appropriate time series data in the second section. Finally lessons will be drawn on the type of shocks and reactions in the BRIC stock markets based on shocks envisaged in the US stock returns and the oil Brent market. The conclusions presented in the last section will complement the analysis with policy making considerations in the matter of financial volatility.

Literature review

BRIC countries, amongst emerging markets continue to represent increased interest for financial investors and economists, though not sufficiently on the volatility of their financial and energy markets. Their potential economic growth for the next thirty years is assumed to make of the BRIC countries the next world economic and financial power. Their resistance to financial crises, i.e. volatility persistence, together with a higher regional financial integration, has made of BRIC countries an interesting case study evidencing the interrelation between financial stability and economic growth. As such, their energy needs together with capital assets increase. The stability over time, of those two variables could determine the country's growth path. Considering evidence on the transmission of volatility between stock markets and oil prices (Malik and Ewing 2009), two explanatory factors are determinant for the rest of the analysis. First, not all BRIC countries have the same energy needs or a similar openness towards financial markets. Second, the level of integration in the regional and world markets impacts financial volatility, which in turn generates instability within the domestic economy. In this regard, the time span of the analysis determines the types of shocks taken into account when analyzing the impact of financial volatility.

The first factor is energy dependency of the BRIC economies. It makes of the energy price stability an important explanatory variable to include in a model assessing financial volatility. Oil prices more particularly have been shown as having a different impact depending on the situation of the country with regards to oil. In the only study of oil markets impact on financial markets volatility in BRIC countries, Bhar and Nikolova (2009a) evidence the influence of oil prices and their volatility on stock returns for BRIC countries, be they net importers or exporters. Microeconomic theory on production costs highlights energy prices as an important determinant for the supply and for the demand side. The increase in production costs fuels inflation. Assuming that national central banks apply anti-inflationary policies, interest rates will increase, rendering stocks less attractive. Thus, stock returns are directly impacted by the relationship a country has with energy prices and its position in the regional and world financial markets. Because of their strong regional integration, China and India stock markets were found not to be influenced by oil prices while Russia stock markets reacted in opposition to oil prices evolution (Bhar and Nikolova 2009a). Three variables are included in the volatility model to be tested in this article. BRIC stock returns are dependent on energy prices and US stock returns. BRIC stock returns are a proxy for financial markets behavior. US stock returns are proxy for integration in the world financial markets. Energy prices are included as a fundamental financial and economic growth factor. Agnolucci (2009) uses GARCH models to forecast light sweet crude oil futures based on the West Texas Intermediate traded at the NYMEX. The data sample span from 31 December 1991 to 2 May 2005. The mean return from oil futures is best approximated by a constant. His explanatory variable is the US risk-free interest rate. The utilized GARCH models are GARCH, APARCH, EGARCH, CGARCH and TGARCH with normal, t-student and GED distributions. APARCH and EGARCH were found to have residual correlation in conditional variance. The tests used to evaluate the models are Q-test on standardized residuals, ARCH and Jarque-Bera tests. The results of the tests show that GARCH(1,1) provides sufficient accuracy. The error distribution type does not affect the value of the GARCH estimated coefficients which fall between 0.95 and 0.96. Shocks are found highly persistent. Meanwhile, TGARCH models estimated with asymmetric terms from 1 to 3 show asymmetry is not important, leading to the conclusion that oil futures are not affected by the leverage effect. Finally GARCH and TGARCH models present serial correlation provoked by the time varying conditional variance. The latter justifies the use of a CGARCH model.

Another paper of interest is the one developed by Bhar and Nikolova (2007) studing financial integration of BRIC countries using data from January 1995 to December 2004 through a two-stage GARCH-in-mean approach. The first stage consists in modelling weekly regional and global equity index returns through ARMA (1,1) and GARCH(1,1)-in-mean with normally distributed errors. The second stage involves squared standardized residuals and introducing them into the mean and volatility equation. Stock market indexes are obtained at the national level (Bovespa for Brazil, AKMI composite for Russia, Sensex for India, Shanghai composite for China) and Morgan Stanley's All countries world index. The regional data consists in Financial Times All countries Europe index, Asia-Pacific index and America's index. Natural logarithm of the price index relative was used to obtain daily equity index returns. Q-test statistic was used to control for serial correlation. It evidences the good fit of the GARCH model with regards to time varying volatility. The other tests show no skewness or kurtosis. Errors are normally distributed. The main result is that volatility of BRIC countries stock indexes is sensitive to the world equity index returns. The correlation is positive for all BRIC countries except for China. Brazil equity returns seem more influenced by the Americas index compared to the world index indirectly illustrating the importance of the US index as the most important component of the Americas index. Similarly, Russian index is impacted by the European index to a higher extent than the world index.

In a recent article, Bhar and Nikolova (2009b) use a bivariate EGARCH model with the same financial indexes extended to October 2006. Negative shocks occur more often for all BRIC countries except for China as evidenced by the existence of skewness and excess kurtosis. Error distribution is not found to be normal. Q test shows the presence of heteroskedasticity in all data. In addition, regional and world data happen to be correlated with all national indexes except in the Chinese case. The results show the dependency of the Brazilian and Indian indexes on regional and world markets with the latter being the most influential for those countries, however the opposite is not true. In the case of the Russian index, the European stock market index is the most influential while the world index seems to be affected by the Russian index. The Chinese stock market index is influenced to a greater extent by the world market index proving indirectly the role of the US stocks, as major contributors to the world index. In addition, asymmetry is higher than one for all indexes. The Russian index seems to be similarly affected by positive or negative shocks. Volatility is persistently present as shown by the HL results with the Brazilian index showing the highest level of persistence (11.52 weeks) while the fastest to recuperate is the Indian market (3.08 weeks). Volatility in the Brazilian case stems from the world market index while it is the negative influence of the regional index in the case of India.

Moreover, the study done by Worthington and Higgs (2004) show that time series volatility in emerging markets present irregularities that are better captured by linear GARCH models. The authors use an MGARCH model with data being the value-weighted equity market indices for Hong Kong, Japan, Singapore, Indonesia, Korea, Malaysia, the Philippines, Taiwan and Thailand. All data is obtained from Morgan Stanley Capital International for the period 15 January 1988 to 6 October 2000. Some markets display similar levels of volatility ranging from 3.19 (Singapore) to 3.72 (Hong Kong). The distribution of the return series is non-normal. The developing markets have negative skewness. Some of the developed markets are negatively skewed while Japan is positively skewed. The conditional variance of the GARCH models result accurate in estimating volatility. The mean own volatility persistence for the developed markets is lower (0.8214) than that of the developing countries (0.8246). In other words, emerging markets are relatively less sensitive to the regional context than the developed markets.

In addition to the general characteristics of time series financial data, financial markets of emerging countries such as BRIC countries (Bhar and Nikolova 2007, 2009a, 2009b) and oil prices volatility, be it in developed countries (Agnolucci 2009) present asymmetry and heteroskedasticity that need to be taken into account. Narayan and Narayan (2007) model crude oil price volatility using daily data for the period 9/13/1991–9/15/2006 the exponential EGARCH model. Their main finding is that shocks have persistent and asymmetric effects on volatility which means that negative and positive shocks have different effects on oil price volatility. But examining sub-samples, they show that over the 1992–1994 period, positive and negative shocks have the same level of impact on oil price volatility. Over the period 5/09/1994–1/08/1996, shocks have asymmetric effects but shocks are not permanent. The post-2001 sub-sample evidences the non-permanent and symmetric effects of shocks on oil price volatility.

Because of the limitation of traditional GARCH models to symmetric volatility to past shocks, non-linear GARCH models have been shown as stronger in the treatment of asymmetry. More particularly GARCH(1,1) and multiple regimes TGARCH models are most accurate for the oil and financial markets asymmetry. Marcelo and Albaro (2009) test a GARCH(1,1), FCGARCH, GJR, EGARCH, and tree-structured GARCH models model using daily logarithm returns of 10 stock indexes: AEX (The Netherlands), ATX (Austria), CAC40 (France), DAX (Germany), FTSE100 (United Kingdom), Hang Seng (Hong Kong), IBOVESPA (Brazil), Nikkei (Japan), SMI (Switzerland) and S&P500 (United States). The approaches used are Bollerslev–Wooldridge QML and the Marquardt algorithm. They find that negative shocks are stickier than positive ones.

To avoid serial correlation, the Iterated Cumulative Sum of Squares algorithm needs to be applied. Fernandez (2004) studies the impact of the Asian crisis and September 11, 2001 events on the major stock markets (Asia, Europe, Latin America and North America) and interest through the ICSS approach. The sample covers the period 1997 to 2002. Data is filtered by a GARCH(1,1) model in order to avoid conditional heteroskedasticity and serial correlation. The standardized residuals are treated with the ICSS before and after the filtering out process. In the latter case, no volatility breakpoints were found for the stock returns and only a few amongst interest rate series. In a second article, the same author (Fernandez 2007) tries an identical method on stock returns indexes on different countries and time period (April 2000 to March 2005). The markets considered are Middle Eastern, African, and Asian countries (Israel, Turkey, Morocco, Egypt, Jordan, Pakistan, Indonesia), developed countries (United Kingdom, Germany, Japan, United States, Spain), and four international indices (Europe, Middle East, Latin America, World, Emerging markets). The sample is then split in two sub-samples in order to check for particular political and economic events: April 2000–December 2001 and January 2002–March 2005. After filtering out data from serial correlation and volatility persistence, the number of structural breakpoints diminished dramatically. The author concludes that the cases when volatility persists are rare. More often volatility clustering is observed, i.e. temporary increase in conditional volatility, except for some Middle Eastern and Asian countries.

Meanwhile, financial crises, financial liberalization or oil shocks in BRIC countries are considered as structural changes to be identified using appropriate tools. The identification of multiple regimes involves complex models. Similarly to the works of Fernandez, Kasman (2009) finds that the inclusion of structural break analysis reduced volatility persistence. He applies ICSS algorithm to stock market indices in BRIC countries from 1990 to 2007. Five indices from the four BRIC countries are considered: Brazil (BOVESPA), Russia (RTS), India (BSE-100) and China (Shanghai (A) and Shenzhen (B)) and are represented by the logarithmic difference of the daily closing index values. The dates and number of breakpoints were detected by using the ICSS algorithm and then introduced in variance to the standard GARCH model. Volatility persistence results are clearly lower.

None of the articles reviewed has given importance to BRIC stock markets volatility as explained by worlds' equity markets volatility, proxied by the US financial index and energy prices in a volatility model such as GARCH, adapted to situations of asymmetric information shocks and volatility persistence. On one hand, the point is made on the importance of the growth path BRIC countries have chosen, which is dependent on the supply and price fluctuations of energy. The latter can foster or hamper resistance to financial shocks as it represents the foundation of the BRIC countries economic performance. On the other hand, reaction to international and domestic swings in equity markets is accurately assessed through the purposeful use of adapted model.

This article explores two approaches widely recognized for their performance in treating issues of serial correlation and heteroskedasticity in time series, namely structural breakpoint identification algorithms and GARCH models. Last but not least, the time period covered in this study running from 1995 to 2009 allows encompassing the most recent developments in financial and energy markets. The multiple events that occurred and are assumed to have impacted the stability of financial trends are studied and their influence evaluated.

Models

Four models are reviewed from a chronological and adaptability perspective. The first two are used to detect the structural breaks in the financial time series considered. The last two GARCH models explore the importance of the breaks on the persistence of volatility over time.

ICSS Algorithm

The Iterated Cumulative Sum of Squares (Inclan and Tiao 1994) allowed to identify abnormal modifications in the variance, i.e. structural breaks. Changes in volatility are also recognized within various regimes of financial time series, separated by distinct threshold value of indicators or variables. The ICSS algorithm identifies the break points, the moments, when the financial regime changes. However, the literature has shown that the ICSS algorithms tend to overstate the number of actual breaks in variance (Fernandez 2004). An additional problem associated with this structural break test is that the ICSS algorithm is questionable under the presence of conditional heteroskedasticity (Fernandez 2007, Sanso et al. 2004). These problems can be solved by filtering the return series by Generalized Autoregressive Conditional Heteroskedasticity models where heteroskedasticity is treated as a variance to be modeled. More precisely, a GARCH (1,1) model and the ICSS algorithm are applied to the standardized residuals. Consequently, this article tests for volatility shifts before and after filtering the data for conditional heteroskedasticity and serial correlation. Alternatively, a second structural break test (Bai and Perron, 2003) is performed with the aim of enforcing the ICSS test results.

The ICSS algorithm assumes that the time series of interest has a stationary unconditional variance over an initial time period until a sudden break takes place. The unconditional variance is then stationary until the next sudden change occurs. This process repeats itself through time, giving time series observations with a number of m breakpoints in the unconditional variance in n observations. To estimate the number of changes and the point of time of variance shifts, a cumulative sum of squared residuals is used. This is denoted as:

$$C_k = \sum_{t=1}^{k} \varepsilon_t^2 \quad (1)$$

where k = 1,…..T, and {εt} is a series of uncorrelated random variables with zero mean and unconditional variance σ_t^2. The variance in each interval is denoted by σ_j^2, with j = 0,1,….., NT, where NT is the total number of variance changes in T observations. By letting $1 < \kappa_1 < \kappa_2 < \dots < \kappa_{N_T} < T$ be the set of breakpoints, the variance is then defined as:

$$\begin{aligned}
\sigma_t^2 &= \sigma_0^2 \quad 1 < t < \kappa_1 \\
&= \sigma_1^2 \quad \kappa_1 < t < \kappa_2 \\
&\dots \\
&= \sigma_1^2 \quad \kappa_{N_T} < t < T
\end{aligned} \quad (2)$$

The statistic DK is defined as follows:

$$D_k = \frac{C_k}{C_T} - \frac{k}{T} \quad \text{with D0 = DT = 0} \tag{3}$$

where CT is the sum of the square residuals from the whole sample period. If there are no changes in variance over the whole sample period, Dk oscillates around zero; otherwise, if there are one or more shifts in variance, Dk will depart from zero. The critical values, which define the upper and lower limits for the drifts under the null hypothesis of stationary variance, determine significant changes in the variance of the series. If the maximum of the absolute value of the statistic Dk is greater than the critical value, the null hypotheses of no sudden changes is rejected. Let k* be the value of k at which $\max_k |D_k|$ is attained, and if $\max_k = \sqrt{(T/2)*|D_k|}$ exceeds the critical values, then k* is taken as an estimate of the change point. The term $\sqrt{(T/2)}$ is used to standardize the distribution. The critical value of 1.358 is the 95th percentile of the asymptotic distribution of $\max_k = \sqrt{(T/2)*|D_k|}$. Therefore, upper and lower boundaries can be set at ±1.358 in the Dk plot.

The ICSS is an iterative approach because the process must be repeated over sub-samples to identify multiple change points. For example, if a point change is observed at τT, then, this point is used to partition the sample into two sub-samples, to τT and (τT+1)-T. The CSS is then estimated over both sub-samples to identify additional point changes. The process is repeated until no new change points are identified.

Bai and Perron Multiple-Breaks

The multiple-breaks test developed by Bai and Perron (2003) consider estimating multiple structural changes in a linear model estimated by least-squares. They derived the rate of convergence and the limiting distributions of the estimated break points. They addressed the important problem of testing for multiple structural changes: a sub Wald type tests for the null hypothesis of no change versus an alternative containing an arbitrary number of changes and a procedure that allows one to test the null hypothesis of, say, ℓ changes, versus the alternative hypothesis of $\ell+1$ changes. The latter is particularly useful as it allows a specific to general modeling strategy to consistently determine the appropriate number of changes in the data.

The model considered is the multiple linear regression model with *m* breaks (or, equivalently, *m+1* regimes).

$$y_i = x_i^T \beta_i + \mu_i \quad (4)$$

$$y_i = x_i^T \beta_i + z_i^T \delta + \mu_i ;\ \textit{where}\ (i = 1, \ldots, n) \quad (5)$$

Where at time *i*, y_i is the observation of the dependent variables, $x_i = (1, x_{i2}, \ldots, x_{ik})^T$ is a *k x 1* vector of observations of the independent variables, with the first component equal to unity, u_i are iid(0,σ²), and β_i is the *k x 1* vector of regression coefficients. Tests on structural change are concerned with testing the null hypothesis of "no structural change"

H0: $\beta_i = \beta_0$ (*i* = 1,…, n)

against the alternative that the coefficient vector varies over time, with certain tests being more or less suitable (i.e., having good or poor power) for certain patterns of deviation from the null hypothesis.

It is assumed that the regressors are non-stochastic with $\|x_i\| = O(1)$ and that,

$$\frac{1}{n} \sum_{i=1}^{n} x_i x_i^T \rightarrow Q \qquad (6)$$

for some finite regular matrix Q.

This analysis allows identifying the number and location of the breakpoints in each series. Once the breakpoints are recognized, they will be included in each econometric model in order to avoid spurious results.

To summarize, the structural break analysis is conducted following two main stages,

1. Initially, the ICSS and Bai and Perron test are applied on individual basis to each series in order to identify breakpoints affecting each variable.
2. Secondly, it is considered of significance to conduct an analysis of each stock market looking at the oil market influence, and therefore, a break test is applied taking into account the impact of oil markets fluctuations on each BRIC stock market. Therefore, the ICSS and Bai and Perron test are adjusted to count for these effects.

The GARCH model

Once the change points in variance have been identified, the GARCH model is estimated without and with sudden changes in variance. Deriving from Autoregressive Conditional Heteroskedasticity (ARCH) models (Engle 1982), GARCH models are best adapted to financial time series analysis with conditional volatility, i.e. time variant. They model volatility as function of lagged squared returns and lagged variances and best capture volatility clustering. Consequently, a GARCH (p,q) model utilizes p as the number of lagged squared returns and q the number of lagged variances. Benefiting from Gaussian and t Student distributions, they allow encompassing different types of variable behaviors.

The standard GARCH (1,1) model as introduced by Bollerslev (1986) lags one squared return and one variance. It is defined for the case without sudden changes as follows:

$$Y_t = \mu + \delta_1 X_{t-1} + e_t \tag{7}$$

where $e_t | I_{t-1}$ ~ N(0, h_t) and h_t is given by the variance equation:

$$h_t = \omega + \alpha e^2{}_{t-1} + \beta h_{t-1} \tag{8}$$

The GARCH(1,1) model with sudden changes and taking into account our variables, is as follows:

$$Y_t = \mu + \delta_1 X_{t-1} + \delta_2 Z_{t-1} + e_t \tag{9}$$

$$h_t = \omega + \alpha e^2{}_{t-1} + \beta h_{t-1} \tag{10}$$

Where:

Yt = Stock Returns (BRIC)

Xt = US Stock Markets Returns (Dow Jones Industrials and S&P500)

Zt = Crude Oil Brent, Natural Gas and Electricity

$e_t | I_{t-1}$ ~ N(0, h_t) and h_t is given by the variance equation

$$h_t = \omega + d_1 D_1 + \ldots + d_n D_n + \alpha e^2{}_{t-1} + \beta h_{t-1} \tag{11}$$

Where D1....Dn are the dummy variables, taking a value of 1 for each point of sudden change in the variance onwards, and of 0 otherwise. Given the modified GARCH model, this incorporates the regime shifts detected by the ICSS algorithms. The persistence of volatility, *i.e.* α + β is predicted to be smaller than that found by the conventional GARCH model.

Therefore, the mean equation will be adjusted as follows:

$$BRICy_t = c_0 + \sum_{t=1}^{m} \alpha_i SMx_{t-i} + \sum_{t=1}^{n} \lambda_i EMz_{t-i} + d_1 bp_1 + ... + d_n bp_n + e_t \varepsilon_{yt} \quad (12)$$

$$h_{yt} = \beta_0 + \sum_{i=1}^{a} \beta_1 h_{yt-1} + \sum_{i=1}^{b} \kappa_1 \mu_{yt-1}^2 \quad (13)$$

We use continuously compounded stock and oil returns calculated as the first difference of the natural log. That is: each variable follow the following transformation, $y_t = \ln(y_t) - \ln(y_{t-1})$. Similarly,

Where $BRICy_t$ = Brazil, Russia, India and China (according to the country under analysis at each time).

SM_x (Stock Market) = Dow Jones Industrials and S&P500

EM_z (Energy Market) = Crude Oil (Crude Oil Brent Index), Gas (Natural Gas-Henry Hub $/MMBTU Index) and Electricity (Nordpool-Electricity Avg. Index)

GARCH models consider positive and negative error terms, or good and bad news, as having a similar effect on volatility. In many cases, volatility reacts more to bad news than good news (Black and Scholes 1973). Thus, the importance of taking into account the asymmetrical reaction to shocks cautions the validity of the GARCH model, and consequently we decide to apply an alternative methodology that counts for this issue.

Asymmetric GARCH

The threshold ARCH model, or TARCH, is one example where positive and negative news are treated asymmetrically. The TGARCH version of the model best captures asymmetry (Sabiruzzaman et al. 2010). The lagged conditional standard deviations, and variance, are introduced as regressors.

The specification of the conditional variance is as follows,

$$y_t = \alpha + \beta y_{t-1} + \varepsilon_t \quad (14)$$

$$y_t = \alpha + \beta y_{t-1} + D_1 BP_1 + ... + D_n BP_n + \varepsilon_t \quad (15)$$

$$y_t = \omega + \lambda x_{t-1} + e_t \quad (16)$$

The above equations are adjusted according to the initial GARCH analysis, as it is possible to appreciate the mean equation used for the T-GARCH estimation is the same that was used for the GARCH analysis.

$$BRICy_t = \omega + \lambda SMx_{t-1} + \varphi EMz_{t-1} + d_1 bp_1 + ... + d_n bp_n + e_t \quad (17)$$

where yt is the stock under analysis (equation 3), and xt the stock market index that in this case has been identified as the S&P500, and finally zt the energy market under consideration at each time. Both equations will be used in order to identify volatility changes and dependencies when oil markets are introduced in the analysis.

$$h_t = \delta + \alpha_1 e_{t-1}^2 + \gamma d_{t-1} e_{t-1}^2 + \beta_1 h_{t-1}; \quad (18)$$

$$\text{where} \quad d_t = \begin{cases} 1 & e_t < 0 \quad \text{(bad news)} \\ 0 & e_t \geq 0 \quad \text{(good news)} \end{cases}$$

where γ is known as the asymmetry or leverage term. When $\gamma = 0$, the model collapses to standard GARCH form. Otherwise, when the shock is positive (i.e. good news) the effect on volatility is α_1, but when the news is negative (i.e. bad news) the effect on volatility is $\alpha_1 + \gamma$. Hence, so long as γ is significant and positive, negative shocks have a larger effect on h_t than positive shocks.

Data and Results Analysis

Throughout this section the data sample selected and the main empirical results obtained are presented and discussed in detail. Firstly, the analysis looks at each series basic properties (structural breaks and unit root analysis) with the aim of obtaining sufficient evidence that guarantee the robustness of the volatility analysis that is conducted at a later stage.

Data Description and Basic Properties

This paper focuses its attention on the investigation of the BRIC stock markets (Brazil, Russia, India and China stock returns) and the effects that some Energy Markets (oil, gas and electricity returns) may have on them. The analysis is conducted over the period January 1995 to December 2009 (3,596 observations per each series). This time period has been selected as it is quite wide and it will allow to pay careful attention to markets behavior during time periods that have been affected by hits in the World economy like: the period of the Asian crisis 1997-1998, the September 11, 2001 terrorist attacks, the dot com bubble that covered 1995-2001 and the Financial Crisis that started on 2007 with the Us Subprime market collapse, and that is extending its effects throughout 2007 and 2009. Consequently, appropriate structural break tests (Bai and Perron and ICSS algorithm) are applied to verify is any of the financial events named above have impacted on the co-movements between the mentioned equity and energy markets. The aim is to analyze the reaction of key emerging economies, during a long period and their interaction with energy markets during a crisis time. Taking into account that the major developed economies has been affected by a serious economic downturn, where financial markets are facing increasing depreciation in their assets, and where commodities and emerging markets are considered fundamental to the world economy recovery process. Therefore, this study driving force is the researchers' belief that the BRIC economies may have suffered to a lesser extent the effects of the economic debacle that has been pressuring the most developed economies, and as a result these economies are becoming more visible than ever as a clear alternative for FDI.

The data examination commence conducting an informal analysis rooted in the graphic representation of each series prices and returns with the aim of identifying initial signs of change on trend on each time series. This early stages are of key importance in order to avoid spurious results that may affect the volatility analysis that is conducted later on. The plots from each series show from the very beginning clear indications of the existence of multiple-breakpoints and non-stationarity issues affecting prices. Such patterns are evidenced by the respective autocorrelation functions, where the processes tend to die out very slowly being necessary to transform prices into returns in order to avoid the presence of unit roots. The next step consist in corroborating the results obtained from the visual analysis, accordingly we move toward the implementation of more formal and sophisticated techniques, like the Augmented Dickey Fuller test in combination with Bai and Perron test and the ICSS algorithm[3] that allow us to identify with clarity if the series are affected by multiple-breakpoints (see table 1 to 3). The results from the Bai and Perron test[4] and the ICSS algorithm show strong evidence of the existence of multiple-breakpoints affecting each regression under analysis. The main characteristic of these tests is the divergence on results obtained from both approaches. While the Bai and Perron test (see table 3) found up to a number of five breaks affecting each regression, the ICSS model is generally limited to a number of three relevant breaks in the case of the Brazil, and up to two breaks in the rest of the cases (China, India and Russia regressions). After analyzing the results and looking at the features of each

[3] See methodology section for further details.
[4] See equation five on the methodology section.

algorithm, it is considered that the ICSS test results provides a more suitable framework for this study, due to the fact that the results from this test have been obtained through the use of a GARCH model. The standard GARCH approach is implemented with the objective of generating the standardized errors that are used later on to identify the number of breakpoints affecting each regression with the help of the ICSS algorithm. On the other hand, the Bai and Perron test is based on a least square approach that does not take into account heteroskedastic patterns affecting each series, and at the same time the results show an overestimation on the number of breaks when compared to the ICSS results. For all these reasons, it is deemed appropriate to conduct the volatility analysis corrected by the ICSS breakpoints rather than the Bai and Perron test.

The next step of the testing consists on splitting up the full sample according to the number of breakpoints identified by the ICSS algorithm (see table 1 and 2). This procedure is of key importance, as in this way it would be possible to add the proper corrections to the GARCH models that will allow the minimization of misspecification errors that will cause spurious results. The results from table 1 and 2 show that in the case of China, India and Russia the regressions are affected by two structural breaks while only in the case of Brazil three breakpoints are estimated significant. The ICSS test used the Dow Jones Industrials and the S&P500 indexes as a proxy variable to control for the effects that the American stock markets may have on each emerging stock market. Additionally, and energy market index (Crude Oil Brent Index, Natural Gas-Henry Hub $/MMBTU Index, and Nordpool-Electricity Avg. Index) is added to capture potential effects derived from energy markets shocks.

The results from the ICSS test (see table 1 and 2) make quite clear that there are insignificant differences between regressions that are using the Dow Jones or the S&P500 index, as the breakpoints identified are very close time-wise. In view of such evidence, the volatility analysis conducted simply takes into consideration the S&P500 index that has a wider representation with regard to the number of companies listed. An important aspect of the results obtained from the breakpoints analysis is the differences that exist between each country. Initially, Brazil seems to be the most volatile market as it is affected by three major shocks. The first shock is identified around October 2002, a period that is characterized by the Brazilian stock market crash. During this time the Brazilian economy was subject to major pressures in the run-up to the presidential election in October 2002, as financial markets were worried about lingering fiscal and current account problems, the crisis in neighboring Argentina, and the prospect of a left-leaning candidate winning the elections. A second breakpoint is detected three years later, in October 2005. This time, it seems that the Brazilian economy is being affected by the instability experienced by markets and that is clearly connected with a hike on oil prices during this year. Finally, a third breakpoint is detected around July 2007 and that can be associated with initial signs of instability on these markets clearly connected to the American financial markets pressures that will be translated later on into the Global Financial crisis. On the other hand, the results for the Chinese, Indian and Russian economies are quite similar, as in these cases only two major structural breaks are detected on each market. In the case of China, the first break is identified around September 1997, a time that is clearly linked to the Asian Crisis and that somehow impacted on the Chinese economy, even though it is necessary to mention that the Chinese economy was one of the few economies considered to be quite unscathed during this time in the Asian region. The other breakpoint affecting this economy is detected around April 2006. At this stage it is possible to argue that the Chinese economy could be suffering a combination of circumstances that may be associated with the energy crisis that affected financial markets during late 2005, and also to some initial signs of the world financial crisis to come from the US economy, where consumption started to slowdown with the clear implications to the Chinese economy considered a major exporter to the US. Finally, the Indian and Russian markets are the ones sharing some common trends. Both identified breakpoints early in 2001 that are clearly connected with the dot com bubble effects, and additionally with the energy crisis that was affecting financial markets during this period. Furthermore, the results show that these markets are also affected by the Global Financial crisis where India sees a structural break around July 2007 and Russia at a later stage in January 2008. Therefore, it seems that China tends to be more impacted by regional volatility on financial and energy markets, while the other countries are influenced by international financial movements.

After identifying the structural breakpoints affecting each country, the next step consists in verifying that each series is stationary, a basic condition that is necessary to confirm if spurious results want to be avoided. Consequently ADF tests are conducted (see table 4) for the full sample and for each subsample obtained from the breakpoint analysis. The results show that all time series returns are stationary for the full sample and for each subsample. These initial results are very reassuring, as the absence of unit roots makes it possible to develop the volatility framework that is discussed in the next section.

Volatility Analysis

This section deals with the results obtained from the GARCH and TGARCH models analyzing volatility patterns on the BRIC stock markets. The analysis tries to identify if the US economy and selected energy markets affect volatility patterns on the BRIC economies. Accordingly, the results discussion is divided in two main sections: i) firstly, the GARCH and TGARCH results per country are discussed in detail, ii) and secondly, a summary of the major findings is outlined.

Brazil

The results for the full sample (see table 5) show that the Brazilian stock market is influenced by shocks affecting the US stock markets and also the oil markets. However, the coefficients representing the impacts from the gas and electricity markets are insignificant during this time period. The results from the standard GARCH form[5], show that during this period the Brazilian stock returns are affected by fluctuations in the US stock markets and that volatility tends to be quite persistent as indicated by a coefficient that is very close to one (0.96) in all three cases. On the other hand, the results from the TGARCH model are very consistent with the standard GARCH. The TGARCH results confirm that the S&P500 returns are also significant in this case, while the coefficients for gas and electricity are proved again to be insignificant. In relation to the variance analysis the α and β coefficients are also positive and significant in line with the initial findings, and the γ coefficient measuring asymmetric information effects, show that negative news have a stronger impact on these markets than positive news. The results obtained from the γ coefficient are quite significant as they will show if the BRIC economies are negatively affected by the different crises detected throughout the ICSS algorithm. According to our structural break analysis, this initial results need to be considered with care as they might be affected by the mentioned breakpoints. Consequently, the GARCH analysis needs to be adjusted according to the number of breakpoints, and therefore rolling windows[6] are used in order to improve the estimations.

The results from the rolling windows adjusted according the breakpoints show that the first (break1) and second (break2) rolling window (see table 5 and 6 respectively) results are quite consistent with the findings for the whole sample, with the exception of the coefficient measuring the significance of oil returns which in this case has been adjusted and it is not found significant. Due to this fact, there is also a minor adjustment with regards to the volatility persistence coefficient that has decreased in between these two periods. The TGARCH analysis is consistent with the GARCH findings and shows that the Brazilian stock market is also affected by negative news during this time period and under the three regressions. Our findings for rolling window three (break3) and four (break4) are in line with the full sample results, where the US stock markets and oil markets returns are found to be significant. In this case we found that the GARCH model for the regression analyzing the impact of oil markets and electricity is not quite appropriate as both α and β coefficients are found to be insignificant. The TGARCH results show that the γ coefficient is significant at 10 percent only in the case of the regression

[5] Where the α and β coefficients are following the $\alpha+\beta<1$ relation that guarantees the variance stationarity.

[6] Brazil presents the highest number of breaks, four in total. Therefore the periods under examination extend from January 1995 to 21/10/2002 for the first one, up to the 28/10/2005 for the second, then up to the 19/07/2007 and finally until December 2009.

including the oil market for break 3 and electricity for break 4 being a result that may be considered quite weak due to the low significance level.

China

The results for the Chinese stock market are very appealing (see tables 5 and 7). The coefficients measuring the impact from the S&P500 are found to be insignificant in the case of the full sample and the rolling windows analyzing breakpoints 1 and 2. With regard to breakpoint 3, there is evidence of a significant coefficient; however the result is quite weak. These initial findings indicate that the Chinese stock market seems to be quite isolated from any shock coming from the US stock markets. Similarly to Bhar and Nikolova's (2009a) findings, the results analyzing the impact of energy markets on the Chinese stock market are also insignificant, with the exception of oil markets results that are found to be significant for breakpoints 1 and 3. The variance analysis shows that both α and β coefficients are lower than one and significant, what means that these markets are affected by volatility persistence, but that might be associated with its domestic markets and probably with the region, but no major impact is coming from energy markets (with the exception of oil) or the US economy. These findings are confirmed by the results obtained from the TGARCH model. In this case the results show that the γ coefficient is found to be positive and significant just in the case of breakpoint 2, deeming as a conclusion that the GARCH model seems to be more appropriate to look at the Chinese stock markets.

India

The Indian case seems to share some similarities with the Brazilian markets. The GARCH analysis for the whole sample (see table 5) shows that this market is affected by turbulences generated in the US stock market but not major impact running from the energy markets where nearly all the coefficients are found to be insignificant. This finding coincides with Bhar and Nikolova's (2009a). With regards to the variance analysis the Indian market is showing variance stability as both coefficients α and β are lower than one, and high volatility persistence, as the coefficient magnitude is closer to one. However, and as it was mentioned for the Brazilian case, these are initial results and the GARCH model needs to be corrected according to the presence of significant structural breaks.

After the GARCH model is adjusted, the results from breakpoint 1 (see table 5) the coefficients measuring the impact from the American stock market appear to be insignificant in all cases, while the coefficient measuring the effects from the electricity index is found to be significant (weak result as it is higher than 5 per cent significance level). The variance analysis shows positive and significant coefficients that are close to one as found for the whole sample. Finally, the results for breakpoint 2 and

3 are very consistent and in line with the results obtained for the whole sample. Therefore, the evidence suggests that the Indian stock market is strongly affected by fluctuations originating from the US stock market. However, energy markets seem to have a marginal influence where only electricity (break 1, see table 1) and oil (break 3, see table 8) are found to be significant in punctual cases. The variance analysis demonstrates that overall, the Indian market suffers from volatility persistence, a characteristic that is also shared by the Brazilian and Chinese stock markets. The results obtained from the TGARCH estimation corroborate the findings from the standard GARCH model. However, in this case it seems that the TGARCH is a more appropriate estimation technique, as indicated by the positive and significant results shown by the γ coefficient. This means that the Indian market is affected by asymmetric information and there is a need to differentiate the impact that positive and negative news may have on this market. Therefore, financial crises may have a stronger impact in this market, a situation that need to be monitored by financial investors in order to minimize their potential losses.

Russia

The Russian stock market behaviour shares some commonalities with the Brazilian and Indian case, as this market is also affected by fluctuations originated in the US stock market, as it can be seen from the results obtained for the full sample (see table 6) and also for breakpoint 2 and 3 (see table 8). Additionally, this is the only market that seems to be affected by the oil and gas market, as significant coefficients are found in the case of the full sample and breakpoint 2 and 3 the oil market, and for break 2 and 3 in the case of the gas market. These results are not surprising, as Russia accounts for around 20 percent of the world's production of oil and natural gas and possesses large reserves of both fuels. Furthermore, the variance analysis shows that volatility persistence is also a quality of this market as evidenced by its positive and significant coefficients. The results obtained for the breakpoint 3 show that the coefficients are equal to 1 what means that the GARCH model converges into an IGARCH model.

The main findings from the TGARCH model are also in line with the standard GARCH estimation, as it has been the case for Brazil, China and India. However, the γ coefficient appears to be insignificant in almost all the cases, meaning that the standard GARCH model is more appropriate to look at volatility patterns in these markets. The same result is shared by the Brazilian and Chinese markets.

In this case, it is important to consider that the Russian market is strongly affected by domestic shocks that are a direct cause of volatility patterns due to the fact that its domestic economy is heavily supported by its natural resources (oil and gas) and is also subject to the international fluctuations, especially the ones originating from the US stock market.

To summarize, it seems that the BRIC economies cannot be considered as a block of countries by investors and that there is a clear need to differentiate volatility patterns among these economies. The results obtained have shown that each market needs to be considered with regards to their regional context and domestic economies. Additionally, it is evident that Brazil, India and Russia share some common patterns, like being influenced by shocks originating from the US stock markets and by energy market fluctuations. Furthermore, it seems that the Indian market is the only one clearly impacted by asymmetric information shocks, as it has been shown by the TGARCH results. Therefore, international shocks may be absorbed quicker by the Indian market rather than by any of the other three markets, a situation that may be translated into higher uncertainty levels on this market. On the other hand, Brazil and Russia are markets that can be considered quite similarly by investors, as these two economies own important reserves of oil and gas, and are also affected by shocks impacting the US economy, a characteristic that may add further pressures on both economies in the case of energy market shocks. Finally, confirming the results of Bhar and Nikolova (2007, 2009b), the Chinese market seems to be quite isolated to external shocks and show a higher level of stability, a characteristic of great value for potential investors. The use of different econometric techniques and an extended time period confirm the conclusions drawn previously on the heterogeneity of the BRIC countries as a group. Deciding on the stability or dependency of a financial market depends on the variables under consideration. Energy prices make a change as well as the level of financial integration in world markets. The study needs further specification of the reasons that allow China to remain isolated from American financial markets and energy prices swings.

Conclusion

Volatility in economics and finance possesses two different meanings. In the first case it is a sign of instability and insertion in the financial world. Some countries are regionally integrated while others present worldwide openers to foreign investment. In the second case volatility represents investment opportunities. Depending on the type of investment objective, short or long term, it will certainly interest investors to know the persistence of volatility over time. Both the economic and the financial perspectives are complementary in that a high level of financial and economic integration is accompanied by investment opportunities. This article puts at work both aspects and extracts the most interesting phenomena in the study of volatility persistence. The additional contribution of this article resides in its focus on countries that present interesting characteristics analyzed in the literature as very promising. In fact, data shows that each of the BRIC countries has its specificities in terms of financial and economic integration and volatility level. The models tested study the relationship between the BRIC national financial indexes as explained by the American financial indices and energy prices. As expected, China is the least integrated country and the least volatile. It can nevertheless not be concluded that less integrated countries are more stable. First, the other countries of the BRIC group are not all volatile at the same level. To affirm that less regional integration leads to the much sought after financial and economic stability, particularly on times of crisis, is only a short run possibility in the international trade theories, which do not need further factual illustration.

Therefore, volatility might as well be a sign of economic openness and challenge of the economy and financial systems of a given country. Growth cycle theories include highs and lows of the financial and economic spheres as part and parcel of macroeconomic mechanisms. Instead, the idea of economic and financial stability needs revision against numerous examples of the opposite. The question still remains on the macroeconomic and financial stability or successful integration in the global market as signs of a sound economy. Is it domestic growth or intensification of international transactions? The truth is the very interrelation of these factors explains the success of an economy. Francoise Lemoine[7] argues that China and India have very different economic structures but are successful in their own way. The Chinese industry has gained international recognition and benefits from strong input from the government. The Indian services sector is booming but the domestic market is based on household consumption while Chinese exports have skyrocketed. Notwithstanding, the Rupee has gradually appreciated while the Chinese Yuan has remained under rigorous control. The financial crisis has had destabilizing effects on the both Indian and Chinese stock markets. The same issues of lack of liquidity were observed.

When considering the relationship between balance of payments stability, public debt and financial transactions in an emerging country, several approaches can be used to contextualize different situations. Firstly, instability can be related to economic and financial institutions transition. Often, authors suggest that the process of convergence towards sustained growth, means a period of instability until the economy finds its growth path. International financial and economic organizations are as active and influential as private investors. In fact, in addition to analyzing FDI levels and progression, the debate now rests on absorption capacities. The latter represent the possibility for a country to assimilate and orient FDI flows. Sound institutions allow for such capacities to develop.

The second approach is based on business cycles. Kondratieff cycles do not exclude the existence of crises of volatility, which are enveloped into a swinging cycle. As a matter of fact, crises are inevitable and are mainly caused by financial instability. The market thus regulates itself and crises are not permanent. The Schumpeterian approach is very similar. The crises are indeed necessary as they purge

[7] Revue d'Economie Financiere, November 2009, 95, 229-41

the market from inefficient mechanisms and benefit innovative and growing activities. But be they temporary or provoking long term changes, crises have an impact on the rest of the financial and economic system. The question is how to overcome the interdependencies between the real and financial spheres. Since the movement of financial deregulation of the 1980s, the two spheres have been isolated from each other and have acquired independence due to the complexity of the financial system and its internationalization.

References

Agnolucci, P. (2009) 'Volatility in Crude Oil Futures: A Comparison of the Predictive Ability of Garch and Implied Volatility Models' *Energy Economics* 31**:** 316-321.

Bai, J. & Perron, P. (2003) 'Computation and Analysis of Multiple Structural Change Models' *Journal of Applied Econometrics* 18**:** 1-22.

Bhar, R. & Nikolova, B. (2007) 'Analysis of Mean and Volatility Spillovers Using Bric Countries, Regional and World Equity Index Returns' *Journal of Economic Integration* 22**:** 369-381.

Bhar, R. & Nikolova, B. (2009a) 'Oil Prices and Equity Returns in the Bric Countries' *World Economy* 32**:** 1036-1054.

Bhar, R. & Nikolova, B. (2009b) 'Return, Volatility Spillovers and Dynamic Correlation in the Bric Equity Markets: An Analysis Using a Bivariate Egarch Framework' *Global Finance Journal* 19**:** 203-218.

Black, F. & Scholes, M. S. (1973) 'The Pricing of Options and Corporate Liabilities' *Journal of Political Economy* 81**:** 637-654.

Bollerslev, T. (1986) 'Generalized Autoregressive Conditional Heteroskedasticity' *Journal of Econometrics* 31**:** 307-327.

Engle, R. F. (1982) 'Autoregressive Conditional Heteroskedasticity with Estimates of the Variance of United Kingdom Inflation' *Econometrica* 50**:** 987-1007.

Fernandez, V. (2004) 'Detection of Breakpoints in Volatility' *Estudios de Administracion* 11**:** 1-38.

Fernandez, V. (2007) 'Stock Market Turmoil: Worldwide Effects of Middle East Conflicts' *Emerging Markets Finance & Trade* 43**:** 58-102.

Inclan, C. & Tiao, G. C. (1994) 'Use of Cumulative Sums of Squares for Retrospective Detection of Changes of Variance' *Journal of the American Statistical Association* 89**:** 913-923.

Kasman, A. (2009) 'The Impact of Sudden Changes on the Persistence of Volatility: Evidence from the Bric Countries' *Applied Economics Letters* 16**:** 759-764.

Malik, F. & Ewing, B. T. (2009) 'Volatility Transmission between Oil Prices and Equity Sector Returns' *International Review of Financial Analysis* 18**:** 95-100.

Marcelo, C. M. & Alvaro, V. (2009) 'Modeling Multiple Regimes in Financial Volatility with a Flexible Coefficient Garch(1,1) Model' *Econometric Theory* 25**:** 117-161.

Sabiruzzaman, M., Monimul Huq, M., Beg, R. A. & Anwar, S. (2010) 'Modeling and Forecasting Trading Volume Index: Garch Versus Tgarch Approach' *Quarterly Review of Economics & Finance* 50**:** 141-145.

Sanso, A., Arago, V. & Carrion-I-Silvestre, J. L. (2004) 'Testing for Changes in the Unconditional Variance of Financial Time Series' *Revista de Economia Financiera***:** 32-53.

Worthington, A. & Higgs, H. (2004) 'Transmission of Equity Returns and Volatility in Asian Developed and Emerging Markets: A Multivariate Garch Analysis' *International Journal of Finance & Economics* 9**:** 71-80.

Appendix

Table 1: ICSS (1994) Structural Breaks by Observations

Brazil-dow-brent	Brazil-sp-brent	Brazil-dow-electricity	Brazil-sp-electricity	Brazil-dow-gas	Brazil-sp-gas
1863	1863	1868	1868	1868	1863
2652	2652	2645	2652	2652	2652
3101	3101	3101	3002	3101	3101
China-dow-brent	**China-sp-brent**	**China-dow-electricity**	**China-sp-electricity**	**China-dow-gas**	**China-sp-gas**
538	538	538	538	538	538
2768	2768	2768	2768	2768	2768
India-dow-brent	**India-sp-brent**	**India-dow-electricity**	**India-sp-electricity**	**India-dow-gas**	**India-sp-gas**
1443	1443	1443	1443	1443	1443
3104	3104	3104	3104	3104	3104
Rusia-dow-brent	**Russia-sp-brent**	**Russia-dow-electricity**	**Russia-sp-electricity**	**Russia-dow-gas**	**Russia-sp-gas**
1394	1394	1430	1394	1430	1394
3227	3227	3227	3227	3227	3227

Table 2: ICSS (1994) Structural Breaks by Date

Brazil-dow-brent	Brazil-sp-brent	Brazil-dow-electricity	Brazil-sp-electricity	Brazil-dow-gas	Brazil-sp-gas
21/10/2002	21/10/2002	28/10/2002	28/10/2002	28/10/2002	21/10/2002
28/10/2005	28/10/2005	19/10/2005	28/10/2005	28/10/2005	28/10/2005
19/07/2007	19/07/2007	19/07/2007	02/03/2007	19/07/2007	19/07/2007
China-dow-brent	**China-sp-brent**	**China-dow-electricity**	**China-sp-electricity**	**China-dow-gas**	**China-sp-gas**
22/09/1997	22/09/1997	22/09/1997	22/09/1997	22/09/1997	22/09/1997
10/04/2006	10/04/2006	10/04/2006	10/04/2006	10/04/2006	10/04/2006
India-dow-brent	**India-sp-brent**	**India-dow-electricity**	**India-sp-electricity**	**India-dow-gas**	**India-sp-gas**
12/03/2001	12/03/2001	12/03/2001	12/03/2001	12/03/2001	12/03/2001
24/07/2007	24/07/2007	24/07/2007	24/07/2007	24/07/2007	24/07/2007
Rusia-dow-brent	**Russia-sp-brent**	**Russia-dow-electricity**	**Russia-sp-electricity**	**Russia-dow-gas**	**Russia-sp-gas**
02/01/2001	02/01/2001	21/02/2001	02/01/2001	21/02/2001	02/01/2001
11/01/2008	11/01/2008	11/01/2008	11/01/2008	11/01/2008	11/01/2008

Table 3: Bai and Perron (2003) Structural Breaks by Observations[8]

Brazil-dow-brent	Brazil-sp-brent	Brazil-dow-electricity	Brazil-sp-electricity	Brazil-dow-gas	Brazil-sp-gas
504	356	479	361	627	310
936	915	918	914	918	918
1777	1774	1775	1761	1775	1563
2559	2166	2151	2903	2126	2860
3169	3372	3375	3360	3318	3338
China-dow-brent	**China-sp-brent**	**China-dow-electricity**	**China-sp-electricity**	**China-dow-gas**	**China-sp-gas**
575	356	582	361	574	309
840	840	841	863	829	861
1378	1577	1422	1548	1427	1548
1767	2083	1764	2902	2027	2858
3158	3174	3178	3362	3218	3340
India-dow-brent	**India-sp-brent**	**India-dow-electricity**	**India-sp-electricity**	**India-dow-gas**	**India-sp-gas**
720	371	738	385	890	378
1271	1224	1559	2112	1555	2094
2298	2280	2126	2664	2126	2663
3031	3012	3048	2913	3048	2900
3246	3370	3333	3347	3238	3264
Russia-dow-brent	**Russia-sp-brent**	**Russia-dow-electricity**	**Russia-sp-electricity**	**Russia-dow-gas**	**Russia-sp-gas**
405	405	710	396	991	606
1189	1611	1597	1578	2681	1655
2703	2952	2901	2946	3027	2861
3018	3111	3040	3112	3116	3111
3276	3330	3279	3355	3266	3276

[8] Breaks by Date table is available upon request.

Table 4: Unit Root Test

ADF	Brazil	China	India	Russia	Dow Jones	S&P500	Brent	Electricity	Gas
Full Sample	-58.92*	-46.83*	-56.54*	-52.83*	-46.69*	-46.83*	-60.58*	-40.81*	-39.13*
	Brazil	**Dow Jones**	**S&P500**	**Brent**	**Electricity**	**Gas**			
Break 1	-41.66*	-42.71*	-42.98*	-43.10*	-30.03*	-12.75*			
Break2	-27.23*	-31.16*	-31.57*	-30.79*	-21.22*	-16.55*			
Break 3	-21.42*	-20.79*	-16.50*	-21.34*	-8.69*	-20.65*			
Break 4	-23.09*	-19.53*	-19.39*	-21.28*	-20.48*	-22.60*			
	China	**Dow Jones**	**S&P500**	**Brent**	**Electricity**	**Gas**			
Break 1	-11.11*	-22.52*	-21.84*	-22.63*	-23.41*	-26.17*			
Break2	-34.87*	-48.04*	-48.55*	-48.75*	-33.53*	-28.08*			
Break 3	-12.58*	-24.90*	-24.88*	-27.88*	-24.67*	-28.50*			
	India	**Dow Jones**	**S&P500**	**Brent**	**Electricity**	**Gas**			
Break 1	-35.72*	-28.15*	-38.07*	-37.88*	-26.32*	-12.67*			
Break2	-19.28*	-42.40*	-42.55*	-42.92*	-33.36*	-24.54*			
Break 3	-20.97*	-19.50*	-19.37*	-21.25*	-19.83*	-22.82*			
	Russia	**Dow Jones**	**S&P500**	**Brent**	**Electricity**	**Gas**			
Break 1	-32.30*	-36.72*	-37.26*	-37.17*	-21.96*	-12.88*			
Break2	-40.67*	-44.84*	-45.31*	-44.89*	-29.41*	-26.13*			
Break 3	-3.99*	-17.11*	-16.90*	-18.41*	-24.57*	-20.52*			

Significance level: *1 per cent, **2 per cent and ***3 per cent

GARCH Model Results

Table 5: Garch Estimation-Whole Sample and Break 1: Brazil, China and India

Wholesample				Break1			
Coefficients	**Brazil-sp-brent**	**Brazil-sp-electricity**	**Brazil-sp-gas**	**Coefficients**	**Brazil-sp-brent**	**Brazil-sp-electricity**	**Brazil-sp-gas**
c0	0.00 (0.00)*	0.00 (0.00)*	0.00 (0.00)*	**c0**	0.00 (0.02)**	0.00 (0.02)**	0.00 (0.02)**
α	0.93 (0.00)*	0.93 (0.00)*	0.93 (0.00)*	**α**	0.80 (0.00)*	0.80 (0.00)*	0.79 (0.00)*
λ	0.05 (0.00)*	0.00 (0.80)	0.01 (0.12)	**λ**	0.00 (0.81)	0.00 (0.51)	0.00 (0.48)
β0	0.00 (0.00)*	0.00 (0.00)*	0.00 (0.00)*	**β0**	0.00 (0.00)*	0.00 (0.00)*	0.00 (0.00)*
β1	0.14 (0.00)*	0.14 (0.00)*	0.14 (0.00)*	**β1**	0.17 (0.00)*	0.17 (0.00)*	0.17 (0.00)*
κ1	0.82 (0.00)*	0.82 (0.00)*	0.82 (0.00)*	**κ1**	0.78 (0.00)*	0.78 (0.00)*	0.78 (0.00)*
β1+ κ1	0.96	0.96	0.96	**β1+ κ1**	0.95	0.95	0.95
Coefficients	**China-sp-brent**	**China-sp-electricity**	**China-sp-gas**	**Coefficients**	**China-sp-brent**	**China-sp-electricity**	**China-sp-gas**
c0	0.00 (0.21)	0.00 (0.20)	0.00 (0.20)	**c0**	0.00 (0.46)	0.00 (0.50)	0.00 (0.49)
α	-0.01 (0.47)	-0.01 (0.47)	-0.01 (0.47)	**α**	-0.03 (0.80)	-0.03 (0.77)	-0.03 (0.77)
λ	0.01 (0.15)	0.00 (0.93)	-0.01 (0.36)	**λ**	-0.13 (0.00)*	-0.02 (0.11)	0.00 (0.68)
β0	0.00 (0.02)*	0.00 (0.02)**	0.00 (0.02)**	**β0**	0.00 (0.03)**	0.00 (0.03)**	0.00 (0.03)**
β1	0.07 (0.00)*	0.07 (0.00)*	0.07 (0.00)*	**β1**	0.22 (0.00)*	0.22 (0.00)*	0.21 (0.00)*
κ1	0.93 (0.00)*	0.93 (0.00)*	0.93 (0.00)*	**κ1**	0.52 (0.00)*	0.53 (0.00)*	0.53 (0.00)*
β1+ κ1	0.99	0.99	0.99	**β1+ κ1**	0.74	0.75	0.74
Coefficients	**India-sp-brent**	**India-sp-electricity**	**India-sp-gas**	**Coefficients**	**India-sp-brent**	**India-sp-electricity**	**India-sp-gas**
c0	0.00 (0.00)*	0.00 (0.00)*	0.00 (0.00)*	**c0**	0.00 (0.52)	0.00 (0.53)	0.00 (0.53)
α	0.10 (0.00)*	0.10 (0.00)*	0.10 (0.00)*	**α**	0.04 (0.34)	0.04 (0.30)	0.04 (0.34)
λ	0.02 (0.16)	0.00 (0.31)	0.00 (0.85)	**λ**	0.00 (0.84)	0.01 (0.056)***	0.00 (0.59)
β0	0.00 (0.00)*	0.00 (0.00)*	0.00 (0.00)*	**β0**	0.00 (0.00)*	0.00 (0.00)*	0.00 (0.00)*
β1	0.11 (0.00)*	0.11 (0.00)*	0.11 (0.00)*	**β1**	0.04 (0.00)*	0.04 (0.01)**	0.04 (0.00)*
κ1	0.88 (0.00)*	0.88 (0.00)*	0.88 (0.00)*	**κ1**	0.94 (0.00)*	0.94 (0.00)*	0.94 (0.00)*
β1+ κ1	0.98	0.98	0.98	**β1+ κ1**	0.98	0.98	0.98

Significance level: *1 per cent, **2 per cent and ***3 per cent. See equations 12 and 13 on the methodology for coefficients details.

Table 6: Garch Estimation-Whole Sample and Break 1: Russia

Wholesample				Break1			
Coefficients	**Russia-sp-brent**	**Russia-sp-electricity**	**Russia-sp-gas**	**Coefficients**	**Russia-sp-brent**	**Russia-sp-electricity**	**Russia-sp-gas**
c0	0.00 (0.00)*	0.00 (0.00)*	0.00 (0.00)*	**c0**	0.00 (0.14)	0.00 (0.15)	0.00 (0.14)
α	0.10 (0.00)*	0.21 (0.00)*	0.21 (0.00)*	**α**	-0.01 (0.66)	0.11 (0.54)	0.11 (0.53)
λ	0.22 (0.00)*	0.00 (0.78)	0.01 (0.37)	**λ**	0.11 (0.53)	0.00 (0.88)	0.00 (0.70)
β0	0.00 (0.00)*	0.00 (0.00)*	0.00 (0.00)*	**β0**	0.00 (0.00)*	0.00 (0.00)*	0.00 (0.00)*
β1	0.14 (0.00)*	0.14 (0.00)*	0.14 (0.00)*	**β1**	0.21 (0.00)*	0.21 (0.00)*	0.21 (0.00)*
κ1	0.85 (0.00)*	0.84 (0.00)*	0.84 (0.00)*	**κ1**	0.75 (0.00)*	0.76 (0.00)*	0.76 (0.00)*
β1+ κ1	0.99	0.99	0.99	**β1+ κ1**	0.97	0.97	0.97

Significance level: *1 per cent, **2 per cent and ***3 per cent

Table 7: Garch Estimation-Break 2 & 3: Brazil & China

Break2				Break3			
Coefficients	**Brazil-sp-brent**	**Brazil-sp-electricity**	**Brazil-sp-gas**	**Coefficients**	**Brazil-sp-brent**	**Brazil-sp-electricity**	**Brazil-sp-gas**
c0	0.00 (0.01)**	0.00 (0.01)**	0.00 (0.014)**	**c0**	0.00 (0.086)***	0.00 (0.44)	0.00 (0.022)**
α	0.93 (0.00)*	0.91 (0.00)*	0.91 (0.00)*	**α**	1.60 (0.00)*	1.71 (0.00)*	1.57 (0.00)*
λ	0.03 (0.13)	0.00 (0.64)	0.01 (0.173)	**λ**	0.11 (0.00)*	-0.01 (0.416)	0.01 (0.194)
β0	0.00 (0.00)*	0.00 (0.03)**	0.00 (0.00)*	**β0**	0.00 (0.046)**	0.00 (0.05)***	0.00 (0.034)**
β1	0.04 (0.058)***	0.04 (0.058)***	0.04 (0.048)**	**β1**	0.14 (0.032)**	0.15 (0.127)	0.14 (0.013)*
κ1	0.88 (0.00)*	0.90 (0.00)*	0.88 (0.00)*	**κ1**	0.68 (0.00)*	0.43 (0.112)	0.73 (0.00)*
β1+ κ1	0.92	0.94	0.92	**β1+ κ1**	0.82	0.58	0.88
Coefficients	**China-sp-brent**	**China-sp-electricity**	**China-sp-gas**	**Coefficients**	**China-sp-brent**	**China-sp-electricity**	**China-sp-gas**
c0	0.00 (0.57)	0.00 (0.57)	0.00 (0.57)	**c0**	0.00 (0.12)	0.00 (0.01)**	0.00 (0.012)**
α	-0.04 (0.08)***	-0.04 (0.08)***	-0.04 (0.08)***	**α**	0.06 (0.18)	0.07 (0.13)	0.07 (0.13)
λ	0.02 (0.10)	0.00 (0.98)	0.00 (0.77)	**λ**	0.05 (0.08)***	0.00 (0.92)	0.00 (0.75)
β0	0.00 (0.00)*	0.00 (0.00)*	0.00 (0.00)*	**β0**	0.00 (0.13)	0.00 (0.13)	0.00 (0.13)
β1	0.16 (0.00)*	0.16 (0.00)*	0.16 (0.00)*	**β1**	0.06 (0.00)*	0.06 (0.00)*	0.06 (0.00)*
κ1	0.71 (0.00)*	0.70 (0.00)*	0.70 (0.00)*	**κ1**	0.93 (0.00)*	0.93 (0.00)*	0.93 (0.00)*
β1+ κ1	0.86	0.86	0.86	**β1+ κ1**	0.99	0.99	0.99

Significance level: *1 per cent, **2 per cent and ***3 per cent

Table 8: Garch Estimation-Break 2 & 3: India & Russia

Break2				Break3			
Coefficients	**India-sp-brent**	**India-sp-electricity**	**India-sp-gas**	**Coefficients**	**India-sp-brent**	**India-sp-electricity**	**India-sp-gas**
c0	0.00 (0.00)*	0.00 (0.00)*	0.00 (0.00)*	**c0**	0.00 (0.39)	0.00 (0.33)	0.00 (0.34)
α	0.06 (0.01)**	0.06 (0.018)**	0.06 (0.01)**	**α**	0.32 (0.00)*	0.36 (0.00)*	0.35 (0.00)*
λ	0.00 (0.97)	0.00 (0.88)	0.00 (0.90)	**λ**	0.17 (0.00)*	0.00 (0.81)	0.03 (0.26)
β0	0.00 (0.00)*	0.00 (0.00)*	0.00 (0.00)*	**β0**	0.00 (0.09)***	0.00 (0.07)***	0.00 (0.07)***
β1	0.14 (0.00)*	0.14 (0.00)*	0.14 (0.00)*	**β1**	0.10 (0.02)**	0.11 (0.02)**	0.10 (0.02)**
κ1	0.79 (0.00)*	0.79 (0.00)*	0.79 (0.00)*	**κ1**	0.84 (0.00)*	0.84 (0.00)*	0.84 (0.00)*
β1+ κ1	0.93	0.93	0.93	**β1+ κ1**	0.95	0.95	0.94
Coefficients	**Russia-sp-brent**	**Russia-sp-electricity**	**Russia-sp-gas**	**Coefficients**	**Russia-sp-brent**	**Russia-sp-electricity**	**Russia-sp-gas**
c0	0.00 (0.00)*	0.00 (0.00)*	0.00 (0.00)*	**c0**	0.00 (0.86)	0.00 (0.72)	0.00 (0.72)
α	0.09 (0.00)*	0.24 (0.00)*	0.24 (0.00)*	**α**	0.37 (0.00)*	0.30 (0.00)*	0.31 (0.00)*
λ	0.25 (0.00)*	0.00 (0.70)	0.01 (0.08)***	**λ**	0.33 (0.00)*	0.00 (0.66)	0.12 (0.00)*
β0	0.00 (0.00)*	0.00 (0.00)*	0.00 (0.00)*	**β0**	0.00 (0.23)	0.00 (0.21)	0.00 (0.22)
β1	0.11 (0.00)*	0.11 (0.00)*	0.11 (0.00)*	**β1**	0.11 (0.00)*	0.13 (0.00)*	0.12 (0.00)*
κ1	0.83 (0.00)*	0.83 (0.00)*	0.83 (0.00)*	**κ1**	0.89 (0.00)*	0.87 (0.00)*	0.88 (0.00)*
β1+ κ1	0.94	0.94	0.94	**β1+ κ1**	1.00	1.00	1.00

Significance level: *1 per cent, **2 per cent and ***3 per cent

Table 9: Garch Estimation-Break 4: Brazil

Break4			
Coefficients	**Brazil-sp-brent**	**Brazil-sp-electricity**	**Brazil-sp-gas**
c0	0.00 (0.19)	0.00 (0.00)*	0.00 (0.15)
α	0.92 (0.00)*	0.98 (0.00)*	0.95 (0.00)*
λ	0.14 (0.00)*	0.00 (0.608)	0.00 (0.97)
β0	0.00 (0.00)*	0.00 (0.00)*	0.00 (0.00)*
β1	0.28 (0.00)*	0.31 (0.00)*	0.30 (0.00)*
κ1	0.56 (0.00)*	0.65 (0.00)*	0.54 (0.00)*
β1+ κ1	0.85	0.96	0.84

Significance level: *1 per cent, **2 per cent and ***3 per cent

T-GARCH Model Results

Table 10: T-GARCH Estimation – Wholesample & Break 1: Brazil, China and India

Wholesample				**Break 1**			
Coefficients	**Brazil-sp-brent**	**Brazil-sp-electricity**	**Brazil-sp-gas**	**Coefficients**	**Brazil-sp-brent**	**Brazil-sp-electricity**	**Brazil-sp-gas**
ω	0.00	0.00	0.00	**ω**	0.00	0.00	0.00
	(0.03)**	(0.025)**	(0.02)**		(0.60)	(0.59)	(0.59)
λ	0.90	0.90	0.90	**λ**	0.79	0.79	0.79
	(0.00)*	(0.00)*	(0.00)*		(0.00)*	(0.00)*	(0.00)*
ρ	0.04	0.00	0.01	**ρ**	0.01	0.00	0.01
	(0.00)*	(0.79)	(0.13)		(0.43)	(0.53)	(0.33)
δ	0.00	0.00	0.00	**δ**	0.00	0.00	0.00
	(0.00)*	(0.00)*	(0.00)*		(0.00)*	(0.00)*	(0.00)*
α1	0.03	0.03	0.03	**α1**	0.01	0.01	0.01
	(0.01)**	(0.01)**	(0.01)**		(0.58)	(0.54)	(0.62)
γ	0.17	0.17	0.17	**γ**	0.23	0.23	0.24
	(0.00)*	(0.00)*	(0.00)*		(0.00)*	(0.00)*	(0.00)*
β1	0.83	0.82	0.83	**β1**	0.80	0.80	0.80
	(0.00)*	(0.00)*	(0.00)*		(0.00)*	(0.00)*	(0.00)*
Coefficients	**China-sp-brent**	**China-sp-electricity**	**China-sp-gas**	**Coefficients**	**China-sp-brent**	**China-sp-electricity**	**China-sp-gas**
ω	0.00	0.00	0.00	**ω**	0.00	0.00	0.00
	(0.55)	(0.52)	(0.54)		(0.37)	(0.34)	(0.40)
λ	-0.01	-0.01	-0.01	**λ**	-0.03	-0.04	-0.04
	(0.49)	(0.49)	(0.49)		(0.77)	(0.72)	(0.73)
ρ	0.01	0.00	-0.01	**ρ**	-0.13	-0.03	0.00
	(0.13)	(0.89)	(0.35)		(0.00)*	(0.07)***	(0.68)
δ	0.00	0.00	0.00	**δ**	0.00	0.00	0.00
	(0.02)**	(0.02)**	(0.02)**		(0.04)**	(0.03)**	(0.04)**
α1	0.05	0.05	0.05	**α1**	0.28	0.31	0.26
	(0.00)*	(0.00)*	(0.00)*		(0.02)**	(0.01)**	(0.02)**
γ	0.03	0.03	0.03	**γ**	-0.09	-0.13	-0.08
	(0.16)	(0.17)	(0.14)		(0.51)	(0.37)	(0.54)
β1	0.93	0.93	0.93	**β1**	0.53	0.53	0.54
	(0.00)*	(0.00)*	(0.00)*		(0.00)*	(0.00)*	(0.00)*
Coefficients	**India-sp-brent**	**India-sp-electricity**	**India-sp-gas**	**Coefficients**	**India-sp-brent**	**India-sp-electricity**	**India-sp-gas**
ω	0.00	0.00	0.00	**ω**	0.00	0.00	0.00
	(0.00)*	(0.00)*	(0.00)*		(0.65)	(0.66)	(0.66)
λ	0.10	0.10	0.10	**λ**	0.03	0.03	0.03
	(0.00)*	(0.00)*	(0.00)*		(0.46)	(0.41)	(0.46)
ρ	0.01	0.00	0.00	**ρ**	0.00	0.01	0.00
	(0.20)	(0.37)	(0.87)		(0.90)	(0.06)***	(0.59)
δ	0.00	0.00	0.00	**δ**	0.00	0.00	0.00
	(0.00)*	(0.00)*	(0.00)*		(0.00)*	(0.04)**	(0.00)*
α1	0.06	0.06	0.06	**α1**	0.03	0.03	0.03
	(0.00)*	(0.00)*	(0.00)*		(0.15)	(0.16)	(0.15)
γ	0.09	0.09	0.09	**γ**	0.08	0.08	0.08
	(0.00)*	(0.00)*	(0.00)*		(0.01)**	(0.01)**	(0.01)**
β1	0.87	0.87	0.87	**β1**	0.86	0.86	0.86
	(0.00)*	(0.00)*	(0.00)*		(0.00)*	(0.00)*	(0.00)*

Significance level: *1 per cent, **2 per cent and ***3 per cent. See equations 17 and 18 on the methodology for detail explanations on the coefficients.

Table 11: T-GARCH Estimation – Wholesample & Break 1: Russia

Wholesample				Break 1			
Coefficients	**Russia-sp-brent**	**Russia-sp-electricity**	**Russia-sp-gas**	**Coefficients**	**Russia-sp-brent**	**Russia-sp-electricity**	**Russia-sp-gas**
ω	0.00 (0.00)*	0.00 (0.00)*	0.00 (0.00)*	**ω**	0.00 (0.22)	0.00 (0.23)	0.00 (0.22)
λ	0.10 (0.00)*	0.21 (0.00)*	0.22 (0.00)*	**λ**	-0.01 (0.65)	0.11 (0.52)	0.11 (0.52)
ρ	0.22 (0.00)*	0.00 (0.77)	0.01 (0.36)	**ρ**	0.11 (0.52)	0.00 (0.88)	0.00 (0.70)
δ	0.00 (0.00)*	0.00 (0.00)*	0.00 (0.00)*	**δ**	0.00 (0.00)*	0.00 (0.00)*	0.00 (0.00)*
α1	0.12 (0.00)*	0.12 (0.00)*	0.12 (0.00)*	**α1**	0.20 (0.00)*	0.20 (0.00)*	0.20 (0.00)*
γ	0.03 (0.36)	0.04 (0.31)	0.04 (0.31)	**γ**	0.02 (0.74)	0.02 (0.75)	0.02 (0.75)
β1	0.85 (0.00)*	0.84 (0.00)*	0.84 (0.00)*	**β1**	0.75 (0.00)*	0.76 (0.00)*	0.76 (0.00)*

Significance level: *1 per cent, **2 per cent and ***3 per cent

Table 12: T-GARCH Estimation –Break 2 & 3: Brazil and China

Break 2				Break 3			
Coefficients	**Brazil-sp-brent**	**Brazil-sp-electricity**	**Brazil-sp-gas**	**Coefficients**	**Brazil-sp-brent**	**Brazil-sp-electricity**	**Brazil-sp-gas**
ω	0.00 (0.04)**	0.00 (0.03)**	0.00 (0.03)**	**ω**	0.00 (0.27)	0.00 (0.62)	0.00 (0.10)
λ	0.91 (0.00)*	0.90 (0.00)*	0.90 (0.00)*	**λ**	1.56 (0.00)*	1.66 (0.00)*	1.54 (0.00)*
ρ	0.03 (0.12)	0.00 (0.83)	0.01 (0.19)	**ρ**	0.10 (0.00)*	0.00 (0.64)	0.01 (0.25)
δ	0.00 (0.00)*	0.00 (0.19)	0.00 (0.00)*	**δ**	0.00 (0.03)**	0.00 (0.10)	0.00 (0.02)**
α1	-0.02 (0.51)	-0.01 (0.59)	-0.01 (0.59)	**α1**	0.04 (0.43)	0.02 (0.65)	0.05 (0.34)
γ	0.08 (0.00)*	0.08 (0.014)**	0.08 (0.01)**	**γ**	0.16 (0.08)***	0.12 (0.26)	0.15 (0.10)
β1	0.88 (0.00)*	0.88 (0.00)*	0.88 (0.00)*	**β1**	0.75 (0.00)*	0.74 (0.00)*	0.77 (0.00)*
Coefficients	**China-sp-brent**	**China-sp-electricity**	**China-sp-gas**	**Coefficients**	**China-sp-brent**	**China-sp-electricity**	**China-sp-gas**
ω	0.00 (0.58)	0.00 (0.61)	0.00 (0.61)	**ω**	0.00 (0.02)**	0.00 (0.02)**	0.00 (0.02)**
λ	-0.04 (0.12)	-0.04 (0.11)	-0.04 (0.11)	**λ**	0.10 (0.21)	0.07 (0.15)	0.07 (0.15)
ρ	0.02 (0.08)***	0.00 (0.93)	0.00 (0.78)	**ρ**	0.01 (0.06)***	0.00 (0.90)	0.00 (0.81)
δ	0.00 (0.00)*	0.00 (0.00)*	0.00 (0.00)*	**δ**	0.00 (0.07)***	0.00 (0.07)***	0.00 (0.07)***
α1	0.09 (0.01)**	0.10 (0.02)**	0.10 (0.02)**	**α1**	0.06 (0.06)***	0.05 (0.06)***	0.05 (0.06)***
γ	0.15 (0.01)**	0.15 (0.013)**	0.15 (0.01)**	**γ**	0.09 (0.39)	0.03 (0.41)	0.03 (0.42)
β1	0.70 (0.00)*	0.70 (0.00)*	0.70 (0.00)*	**β1**	0.87 (0.00)*	0.92 (0.00)*	0.92 (0.00)*

Significance level: *1 per cent, **2 per cent and ***3 per cent

Table 13: T-GARCH Estimation –Break 2 & 3: India

Break 2				Break 3			
Coefficients	**India-sp-brent**	**India-sp-electricity**	**India-sp-gas**	**Coefficients**	**India-sp-brent**	**India-sp-electricity**	**India-sp-gas**
ω	0.00 (0.00)*	0.00 (0.00)*	0.00 (0.00)*	**ω**	0.00 (0.81)	0.00 (0.63)	0.00 (0.65)
λ	0.07 (0.00)*	0.07 (0.00)*	0.07 (0.00)*	**λ**	0.32 (0.00)*	0.36 (0.00)*	0.35 (0.00)*
ρ	0.00 (0.88)	0.00 (0.88)	0.00 (0.66)	**ρ**	0.18 (0.00)*	0.00 (0.84)	0.06 (0.02)**
δ	0.00 (0.00)*	0.00 (0.00)*	0.00 (0.00)*	**δ**	0.00 (0.09)***	0.00 (0.08)***	0.00 (0.06)***
α1	0.01 (0.75)	0.01 (0.75)	0.01 (0.76)	**α1**	0.00 (0.79)	0.02 (0.55)	-0.01 (0.50)
γ	0.22 (0.00)*	0.22 (0.00)*	0.22 (0.00)*	**γ**	0.16 (0.00)*	0.14 (0.01)**	0.15 (0.00)*
β1	0.78 (0.00)*	0.78 (0.00)*	0.78 (0.00)*	**β1**	0.87 (0.00)*	0.86 (0.00)*	0.87 (0.00)*

Significance level: *1 per cent, **2 per cent and ***3 per cent

Table 14: T-GARCH Estimation –Break 2 & 3: Rusia

Break 2				Break 3			
Coefficients	**Russia-sp-brent**	**Russia-sp-electricity**	**Russia-sp-gas**	**Coefficients**	**Russia-sp-brent**	**Russia-sp-electricity**	**Russia-sp-gas**
ω	0.00 (0.00)*	0.00 (0.00)*	0.00 (0.00)*	**ω**	0.00 (0.42)	0.00 (0.79)	0.00 (0.77)
λ	0.09 (0.00)*	0.24 (0.00)*	0.23 (0.00)*	**λ**	0.38 (0.00)*	0.32 (0.00)*	0.32 (0.00)*
ρ	0.24 (0.00)*	0.00 (0.73)	0.01 (0.09)***	**ρ**	0.33 (0.00)*	0.00 (0.68)	0.11 (0.01)**
δ	0.00 (0.00)*	0.00 (0.00)*	0.00 (0.00)*	**δ**	0.00 (0.12)	0.00 (0.13)	0.00 (0.15)
α1	0.08 (0.00)*	0.08 (0.00)*	0.08 (0.00)*	**α1**	0.04 (0.13)	0.06 (0.05)***	0.07 (0.03)**
γ	0.06 (0.12)	0.07 (0.07)***	0.07 (0.07)***	**γ**	0.12 (0.05)***	0.12 (0.07)***	0.10 (0.13)
β1	0.82 (0.00)*	0.81 (0.00)*	0.81 (0.00)*	**β1**	0.90 (0.00)*	0.87 (0.00)*	0.88 (0.00)*

Significance level: *1 per cent, **2 per cent and ***3 per cent

Table 15: T-GARCH Estimation –Break 4: Brazil

Break 4			
Coefficients	**Brazil-sp-brent**	**Brazil-sp-electricity**	**Brazil-sp-gas**
ω	0.00 (0.26)	0.00 (0.019)**	0.00 (0.25)
λ	0.92 (0.00)*	0.97 (0.00)*	0.94 (0.00)*
ρ	0.14 (0.00)*	0.00 (0.51)	0.00 (0.98)
δ	0.00 (0.00)*	0.00 (0.00)*	0.00 (0.00)*
α1	0.24 (0.016)**	0.20 (0.01)**	0.21 (0.03)**
γ	0.09 (0.46)	0.19 (0.07)***	0.14 (0.21)
β1	0.58 (0.00)*	0.66 (0.00)*	0.58 (0.00)*

Significance level: *1 per cent, **2 per cent and ***3 per cent