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The volatility behavior of emerging BRICS stock markets

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Abstract: *Ever since the world economies adopted the liberalization process, the emerging economies and the group of emerging economies especially BRICS have gained its importance due to their size and potential for growth in various sectors of their economies. In this paper we have undertaken the study of volatility behavior of BRICS stock markets as it is very crucial for investment decisions. The closing prices of the indices BOVESPA, MICEX, SENSEX, SSE, and FTSE/JSE were collected from 31st march 2005 to 31st march 2015. Further, this sample period is sub divided into three periods to represent the Pre Crisis, Crisis and Post Crisis period of global financial crisis of 2008. The volatility persistence is observed in all the five indices for all the periods by using GARCH(1,1) model and asymmetric effects observed in all the indices except for China by using GJRGARCH(1,1) model and News impact curve analysis.*

JEL Classification: F30, G10, G15

Keywords: Volatility persistence, BRICS Markets, GARCH models, News impact curves

Introduction

It's a well-known fact that the recent economic, financial reforms taken up by the emerging economies around the globe have placed them on the different arena of the financial world. The capital markets reforms in emerging economies have provided major investment opportunities to the rest of the world. With the increasing investments in the emerging capital markets, they could witness a paradigm shift in their market capitalization, the number of listed companies and the value of shares traded. In spite of the growth of these markets, they are considered highly volatile which may act as a potential barrier for investments, especially with the growing financial integration. Volatility in the prices of stock adversely affects individual's earnings, profits of the companies, investment decisions and health of the economy. Increase in volatility creates an uncertain atmosphere there by dampening the consumption and investments of the firms. Hence, the development of markets coupled with the inevitable volatility in emerging markets has become a matter of great concern to all the investors as well as researchers.

The pioneering work of Fama (1965) on the stock prices raised the interest of all financial, economic researchers to understand the characteristics of financial data. The volatility of stock returns in the developed countries has been studied extensively after the stock markets crash in 1987. Giorgio De Santis and Selahattin Imrohoroglu (1994) studied the dynamic volatility behavior of a few developing countries using the weekly data for the time period from December 1988 to May 1994. The results of the GARCH model showed that all the countries

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have the time-varying volatility and high level of persistence in volatility. Victor Murinde and Sunil Poshakwale (2001) investigated the main features of stock market volatility in the emerging market of European transition economies using daily indices for the period of December 1997 to April 2000. The symmetric and asymmetric GARCH models used for the analysis found that the European emerging markets have volatility persistence, but, no asymmetric volatility effects for most of the markets. Sunil Poshakwale and Victor Murinde (2001) found that the GARCH models outperform the conventional OLS to capture the volatility of Hungarian and Polish stock markets for the time period January 1991 to April 1994 using the daily prices. Ramaprasad Bhar and Biljana Nikolova(2007) studied the degree of integration, volatility spillover effects of the BRIC markets on a regional and global basis . They have used ARMA (1, 1) - GARCH (1, 1) for the daily data over the period from January 1995 to December 2004 and found that among the BRIC countries only China has the negative relationship between volatility spillover effects. Panayiotis F. Diamandis(2008) examined the dynamic behavior of stock market volatility for the emerging markets and a developed market(US), by taking the weekly data for the period 1988-2006 (includes Asian, Latin American and Russian financial crises) with SWARCH-L model. The results of the study showed that there was a significant increase in the volatility during the period of crisis for all the markets. Fazeel M. Jaleel and Lalith(2009) observed the higher volatility during the liberalization period for the Sri Lanka market. They have used TGARCH model and showed that there is no leverage effect for the Sri Lankan companies for the sample period. Ping Wang and Tomoe Moore (2009) studied the sudden changes in volatility of new European Union emerging member's stock markets using weekly data over the period 1994-2006. They have found that the volatility persistence is reduced significantly after taking sudden shifts into account with GARCH models. Kedar nath Mukherjee and Rma kumar Mishra(2010) have studied the stock market integration and volatility spillover between India and its major Asian counterparts for the period 1997-2008 using Intraday prices. The results of the GARCH model showed that the intraday returns were positively significant and bi-directional with all the markets. Chkili Walid, Aloui Chaker, Omar Masood and John Fry (2011) have investigated the impact of FX rate changes on stock market volatility, using two regime Markov switching-EGARCH model in "calm" and "turbulent" periods for four emerging markets during 1994-2009. The results indicated that foreign exchange rate changes have a significant impact on the probability of transition across regimes. Similar study by Slah and Fathi(2014) investigated the behavior of time-varying volatility in 11 middle East and North African(MENA) countries using three-state model(tranquil period, turmoil regime with high volatility, crisis regime) over the period from 2006-2011. The conditional volatility is modeled by using an autoregressive GARCH (1, 1) and found the spillovers from the MSCI world index to MENA stock markets across different regimes. Granger causation effect from MSCI world index to MENA stock markets is stronger in crisis regime across the three stage model.

The BRIC acronym was coined by the Chief Economist of Goldman Sachs, Jim O Neil in the year 2001 with all developing and fast growing economies of G-20 members. With the induction of South Africa in 2010 on account of its growing importance in the world economy, the new BRICS group was formulated. This group representing the collective power of Brazil, Russia, India, China and South Africa has around 40% of the world population, the combined nominal GDP of US$16.6 trillion which is 22% of world GDP, and with combined foreign reserves of US$4 trillion. These economies have a significant role in the world economy as producers of goods and services, receivers of capital, and as potential consumer markets with a

growing middle income families. Each of these countries has a huge potential in its own capacities- Brazil and Russia are noted for the supply of raw materials, Oil, natural gas and minerals. India and China are the dominant suppliers of services and manufacturing goods with highly skilled workforce, while South Africa is known for mineral, metal reserves and cheapest electricity generation in the world. All these five countries liberalized their capital markets in the early 1990s. Brazil liberalized its stock market in 1991, Russia in 1994, India in 1992, China in 1993 and South Africa in 1996. The liberalization policy in these markets paved the way for huge capital flows and eventually became a global investment destinations to the world economies. Furthermore, these markets are globally integrated with other emerging as well as developed markets.

The growth of market development indicators of BRICS markets along with USA market is shown in Table 1. In terms of market capitalization, the share of BRICS economies is greater among the world markets and it's also evident from individual countries volume that all the BRICS economies witnessed a surge in the last decade. However, in case of depth of stock markets measured in terms of market capitalization to GDP in BRICS economies, India, China, South Africa and USA markets progressively deepened in the last ten years while Brazil and Russia markets experienced a downturn. Between the BRICS, USA markets South Africa had the largest market capitalization relative to GDP in 2005 and 2015. The turnover ratio used to measure the liquidity situation in the markets jumped in all the BRICS countries and USA except Russia and India with a fall from 27% and 83% in 2005 to 22.43% and 50% in 2016. The number of companies domestically incorporated in stock exchanges declined from 2005 to 2016 in Brazil, Russia and South Africa of the BRICS economies and in USA. With regard to India and China there was an increase in the number of listed domestic companies. It has been expected that these five countries will continue to grow in their size and they account for 40% of the world's market capitalization by 2030, and China may surpass the USA's market capitalization. Though these markets are growing in tandem with each other in a group, they differ from each other in terms of their economic, structural and institutional factors. For instance, the degree of capital market openness in China and India is less open and more state controlled, while Brazil, Russia and South Africa are less state controlled and more open to the world economies.

It is a well-known fact that all the stock markets are driven by the information that flows in the economy. The markets are said to be efficient only when the stock prices incorporate and reflect all the information that is available in the market. Hence, any asymmetry in the information would result in excess volatility of prices. The information flow into the market depends on the institutional order of the country and it is not uniform in all the countries i.e. developing and developed countries. In this context, the present paper aims to examine whether the five emerging markets have volatility asymmetry and the impact of information flow on the equity market volatility.

Though there are few studies on the volatility behavior of emerging stock markets in general (see for example J.Fabozzi, Radu Tunaru and Tony Wu(2004), Benjamin M. Tabak and Solange M. Guerra (2007), Trilochan Tripathy, and Luis A. Gli-Alama(2015). But, there are no studies have in the context of BRICS economies as a group in particular. In the light of this background, it would be of interest to examine the volatility behavior of this group of emerging market economies.

This paper is organized as follows: the first section introduces and motivates the importance of the study of the behavior of the stock market's volatility in BRICS. The second

section gives the data and methodology. In the third section, we discuss the results of the study. The following section presents summary and concluding remarks of the study.

Table 1: Market Capitalization, liquidity, Turnover and Listed companies for BRICS&USA Markets

	Market Capitalization				Turnover ratio			
	(US$)		% of GDP		Value of shares traded as a % of Market Capitalization		Listed Companies	Domestic
Country	2005	2016	2005	2016	2005	2016	2005	2016
Brazil	4.75E+11	7.59E+11	53.21	42.23	36.01	73.96	342	338
Russia	5.49E+11	6.22E+11	71.80	48.47	26.95	22.43	414	242
India	5.53E+11	1.56E+12	68.37	69.21	83.86	50.55	4763	5820
China	4.02E+11	7.32E+12	17.57	65.37	97.63	273.22	1377	3052
South Africa	5.49E+11	9.51E+11	213.09	322.65	20.26	42.30	348	303
USA	1.7E+13	2.74E+13	129.83	147.29	151.71	154.78	5145	4331

(Source: World Development Indicators Database)

Data and Methodology

The present study is based on daily observations of stock indices of five emerging markets namely Bovespa (Brazil), Micex (Russia), BSE Sensex (India) ,SSE Composite Index (China), FTSE /JSE (South Africa). The closing prices data of Brazil, China and India is obtained from the Yahoo finance database. Russia and South Africa data are collected from Micex site and WSJ site respectively. The sample period is from 31 March 2005 to 31 March 2015. In order to see the impact of 2008 financial crisis on these selected markets the data is further divided into Pre crisis period from 31 March 2005 to 31 March 2008, Crisis period from 31 March 2008 to 31March 2010 and Post crisis period from 31 March 2010 to 31 March 2015. The returns of all these indices are calculated by using formula

$$R_t = \log\left(\frac{p_t}{p_{t-1}}\right) \times 100$$

Where log is the natural logarithm, p_t and $p_{t-1}$are the closing prices at period (t) and (t-1) respectively.

Volatility Modeling

Ever since Engle (1982), Bollerslev (1986) introduced the ARCH and GARCH models, variety of models with different characteristics have been introduced. The existing models broadly can be divided into two categories: Symmetric and Asymmetric models. In symmetric models, the conditional variance depends only on the magnitude, not the sign of the underlying asset. This property is seldom in accordance with empirical results where a leverage effect often is present i.e. volatility increases more after negative return shocks than after the positive return shocks of the same magnitude. Otherwise, bad news generates higher volatility more than the good news. The general GARCH (p, q) model is as follows:

$$\sigma_t^2 = c + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 \text{ .....(1)}$$

The model includes one ARCH term (ε_{t-i}^2) and one GARCH $\left(\sigma_{t-j}^2\right)$term. The sum of α and β coefficients governs the persistence of volatility shocks in the model.

Even though the GARCH model has the capability to capture thick tailed returns, volatility clustering is not well suited to capture the leverage effect since the conditional variance is a function only of the magnitudes of the lagged residuals and not their signs.

GJR GARCH (p, q)

In the GARCH (p, q) model, the conditional variance is specified as a linear function of past squared errors and past conditional volatility. The linear GARCH model does not capture the asymmetric changes in stock return volatility. This asymmetry is now a well-known feature of financial markets: bad news causes a higher volatility than good news of the same magnitude, and this has been interpreted as due to a leverage effect (Black, 1976: Christie, 1982). The leverage effect suggests that when stock prices decline due to negative shocks, the leverage of the firm increases leading to higher stock price volatility. So as to accommodate this asymmetric response, Glosten, Jagannathan and Runkle (1993) have introduced the model and is known as the GJR GARCH (p, q) model. The Conditional variance of the GJR GARCH model is specified as follows:

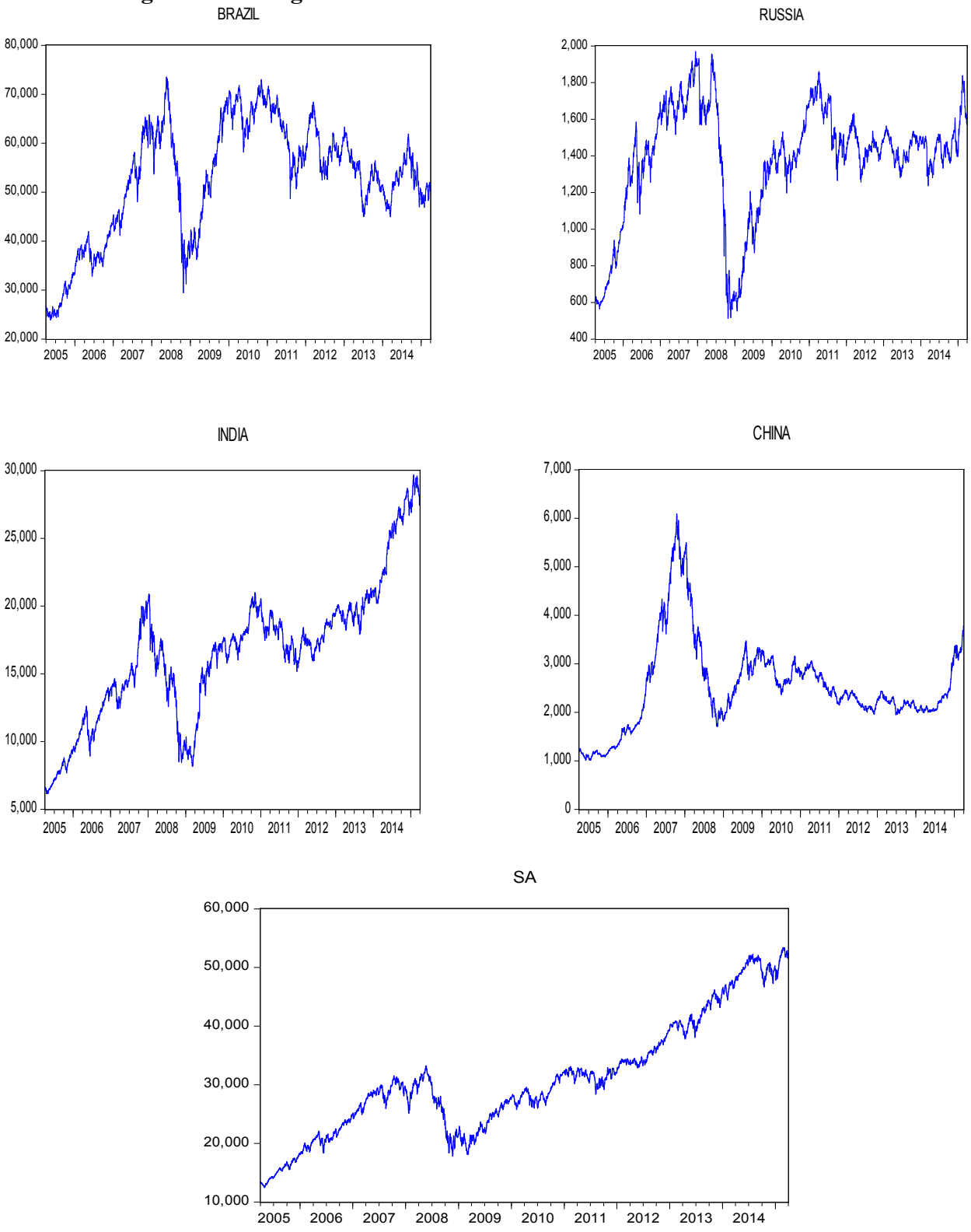
$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \gamma_i I_{t-i} \varepsilon_{t-i}^2 + \sum_{k=1}^{r} \beta_i \sigma_{t-i}^2 \text{.....(2)}$$

Is the asymmetric or leverage effect and I_{t-1} is the dummy variable used to differentiate the good and bad news i.e., $I_{t-1} = 1$ if $\varepsilon_{t-1} < 0$ indicating bad news, and $I_{t-1} = 0$ if $\varepsilon_{t-1} \geq 0$ indicating good news. The GJR GARCH model specification assumes that unexpected changes in the market returns or ε_t will have difference effect on the volatility of stock return, σ_t^2. Good news will lead to higher return; hence it is associated with higher variance through γ. A non-zero value of γ indicate the asymmetric nature of the returns. On the other hand, when γ is zero, we get back to the standard symmetric GARCH model.

Empirical results

In this section we discussed the empirical results of data for BRICS stock markets. The closing prices of these markets which considered in this study have been shown as five time series plots in figure 1. It has been observed that with the impact of the financial crisis during the end of 2008 all the markets have experienced a sudden fall in varied degree.

Figure 1: Closing Prices of the BRICS Stock Markets from 2005-2015



Descriptive Statistics

The summary statistics of all the return series of the indices of the study are presented in the table 2.

Table 2: Descriptive Statistics of Returns

Variable	Mean	Std. Dev.	Skewness	Kurtosis	J-B	ARCH-LM (at Lag=5)
BOVESPA-Full Sample	0.025	1.741	-0.042	9.305	4320.824	162.766(P=0.000)
BOVESPA-Sub Period1	0.106	1.611	-0.386	4.202	66.547	7.811(P=0.000)
BOVESPA-Sub Period2	0.027	2.538	0.101	8.247	599.697	34.982(P=0.000)
BOVESPA-Sub Period3	-0.024	1.388	-0.094	4.747	167.692	21.540(P=0.000)
MICEX-Full Sample	0.038	2.158	-0.173	23.498	45671.440	77.122(P=0.000)
MICEX –Sub Period1	0.128	1.850	-0.488	6.525	436.023	30.505(P=0.000)
MICEX –Sub Period2	-0.022	3.664	0.054	13.110	2223.400	12.340(P=0.000)
MICEX –Sub Period3	0.009	1.376	-0.810	8.799	1969.557	9.619(P=0.000)
SENSEX-Full Sample	0.056	1.494	0.059	11.967	8739.591	42.548(P=0.000)
SENSEX-Sub Period1	0.112	1.559	-0.499	6.437	417.378	28.109(P=0.000)
SENSEX-Sub Period2	0.022	2.238	0.355	9.288	871.054	3.469(P=0.004)
SENSEX-Sub Period3	0.036	1.001	-0.043	3.875	41.969	9.521(P=0.000)
SSE- Full Sample	0.044	1.616	-0.359	7.095	1878.241	29.223(P=0.000)
SSE-Sub Period1	0.138	1.779	-0.709	6.725	517.590	7.031(P=0.000)
SSE-Sub Period2	-0.021	2.193	0.013	4.750	66.634	5.293(P=0.000)
SSE-Sub Period3	0.014	1.181	-0.438	6.786	820.593	11.652(P=0.000)
FTSE/JSE-Full Sample	0.052	1.243	-0.204	7.131	1872.813	129.116(P=0.000)
FTSE/JSE-Sub Period1	0.102	1.244	-0.333	5.779	266.045	26.128(P=0.000)
FTSE/JSE-Sub Period2	-0.006	1.804	-0.071	5.236	109.184	24.272(P=0.000)
FTSE/JSE-Sub Period3	0.046	0.927	-0.162	4.903	202.569	16.901(P=0.000)

The average of the returns for the five indices across all the time periods has been positive except in Sub Period3 of Brazil, during Sub Period2 of Russia, China, and South Africa. We can observe that the standard deviation for all the indices is high during the Sub Period2 which indicates that the BRICS markets were affected by the financial crisis. The series also exhibited an excess kurtosis of above 3, indicating that the returns are not normally distributed. The hypothesis that log returns are normally distributed is tested using the Jarque-Berra test statistic and the results confirm that the null hypothesis of normality is rejected at the significance level of 5%. The presence of ARCH effect in the data series is evident from the statistically significant LM test statistics which has been conducted up to 5^{th} lag for all the five markets at all periods. Non- normality is a reason for attempting asymmetric GARCH models like TGARCH which is better indicator of asymmetries in volatility. In order to check the

stationarity of the return series we employed the Augmented Dickey – Fuller (ADF) as well as Phillips Perron(PP) tests and the results of these tests are presented in table 3. The results show that all the five stock returns of these indices are stationary at levels.

Table 3: Results of Unit Root Tests

Variable	Intercept & Trend		Stationary Level
	ADF Test Statistic	PP Test	
BOVESPA	-37.1517	-52.1801	I(0)
MICEX	-35.6559	-50.3328	I(0)
SENSEX	-35.4011	-46.966	I(0)
SSE	-36.2162	-51.0688	I(0)
FTSE/JSE	-36.7135	-50.1884	I(0)

Estimation of GARCH

To know the volatility persistence of these indices we have used the GARCH model and found that GARCH (1, 1) is a good fit for all the five indices in all the periods by using AIC criterion. Which is the general observation of many researchers (for example see Brooks, C and Burke, S.P (2003)). The estimation results of GARCH (1, 1) were presented in table 4.

It is evident from the table 4, that the volatility persistence estimate given by the sum of the ARCH and GARCH term is high in all the indices for all the periods except for SSE in Sub Period3 (0.770045). The volatility persistence is very high ($\alpha + \beta \geq 1$) for MICEX and SENSEX during Sub Period2. This implies that shocks die out very slowly in all the five indices. The ARCH term that provides the news about the previous day's volatility is high for these indices except for SSE in Sub Period3. This indicates that revision of volatility due to shocks to new/latest information is faster in all the counties but not in SSE during Sub Period3. The estimates of previous day's variances are given by the GARCH term for all indices is high and significant for all the five indices during all the periods.

Table 4: Estimation Results of GARCH (1, 1)

Variable	CONSTANT	ARCH TERM(α)	GARCH TERM(β)	α + β
BOVESPA-Full Sample	0.06101 (3.482)	0.07630 (6.280)	0.90045 (57.210)	0.97675
BOVESPA-Sub Period1	0.18365 (2.132)	0.08784 (3.155)	0.84283 (16.943)	0.93067
BOVESPA-Sub Period2	0.05861 (1.347)	0.10452 (3.578)	0.88693 (30.667)	0.99145
BOVESPA-Sub Period3	0.05580 (2.321)	0.06307 (4.038)	0.90782 (38.231)	0.97089
MICEX-Full Sample	0.05429 (3.940)	0.10487 (7.456)	0.88265 (62.598)	0.98752
MICEX –Sub Period1	0.15858 (2.656)	0.15666 (4.243)	0.79997 (19.225)	0.95663
MICEX –Sub Period2	0.05854 (0.943)	0.12393 (4.332)	0.87988 (36.873)	1.00381
MICEX –Sub Period3	0.045531 (2.790)	0.066421 (3.866)	0.910656 (43.578)	0.977077
SENSEX-Full Sample	0.025175 (3.337)	0.096810 (7.134)	0.892791 (62.700)	0.989601
SENSEX-Sub Period1	0.09205 (2.472)	0.16652 (3.606)	0.80097 (15.886)	0.96749
SENSEX-Sub Period2	0.02064 (0.797)	0.13587 (3.428)	0.87368 (26.198)	1.00955
SENSEX-Sub Period3	0.013018 (1.780)	0.050641 (3.872)	0.937211 (55.410)	0.987852
SSE- Full Sample	0.015135 (2.137)	0.050084 (4.798)	0.946295 (86.240)	0.996379
SSE-Sub Period1	0.02460 (1.274)	0.07112 (3.315)	0.92671 (43.661)	0.99783
SSE-Sub Period2	0.05171 (1.081)	0.07890 (2.810)	0.91141 (30.391)	0.99031
SSE-Sub Period3	0.328699 (1.570)	0.068342 (1.867)	0.701703 (4.134)	0.770045
FTSE/JSE-Full Sample	0.01685 (3.323)	0.09874 (7.662)	0.89118 (66.771)	0.98992
FTSE/JSE-Sub Period1	0.05016 (2.436)	0.11590 (4.591)	0.85307 (28.138)	0.96897
FTSE/JSE-Sub Period2	0.009947 (0.854)	0.099029 (4.040)	0.899740 (40.144)	0.998769
FTSE/JSE-Sub Period3	0.016337 (2.290)	0.084327 (4.492)	0.897869 (41.008)	0.982196

Estimation of GJR-GARCH

The GJR-GARCH or TGARCH model is employed to see the leverage effect in the markets. The leverage effect is the evidence for negative news having a bigger impact on volatility than the positive news. The leverage effect is often described as a falling equity price which leads to an increase in a firm's debt to equity ratio which increases the volatility of returns to equity holders. The GJR-GARCH model is found to be suitable for all the five indices by using AIC criterion. The results are given in the following table 5.

Table 5: Estimation Results of GJR-GARCH (1, 1)

Variable	Constant	ARCH TERM(α)	LEVERAGE(γ)	GARCH TERM(β)
BOVESPA-Full Sample	0.069203 (3.835)	0.009054 (0.848)	0.116406 (5.266)	0.904411 (54.809)
BOVESPA-Sub Period1	0.25968 (2.7292)	0.000000 (0.00000)	0.18251 (2.922)	0.80149 (13.972)
BOVESPA-Sub Period2	0.061157 (1.50517)	0.028476 (0.970)	0.130208 (2.478)	0.892507 (32.138)
BOVESPA-Sub Period3	0.049828 (2.568)	0.000000 (0.000000)	0.106853 (4.281)	0.921753 (41.977)
MICEX-Full Sample	0.060812 (4.266)	0.059241 (4.2698)	0.087537 (3.907)	0.880727 (62.349)
MICEX –Sub Period1	0.197566 (2.802)	0.078746 (2.194)	0.145939 (2.391)	0.786185 (17.375)
MICEX –Sub Period2	0.066559 (1.033)	0.060153 (1.923)	0.095487 (2.127)	0.891103 (36.688)
MICEX –Sub Period3	0.056697 (2.954)	0.006275 (0.40398)	0.098186 (3.421)	0.912043 (42.237)
SENSEX-Full Sample	0.033018 (4.080)	0.025240 (2.291)	0.148801 (5.616)	0.884816 (60.820)
SENSEX-Sub Period1	0.160340 (4.253)	0.014709 (0.447)	0.412842 (3.865)	0.709160 (14.539)
SENSEX-Sub Period2	0.014800 (0.687)	0.019643 (0.980)	0.147410 (3.402)	0.905652 (38.254)
SENSEX-Sub Period3	0.030340 (2.892)	0.000000 (0.000000)	0.133003 (4.047)	0.904936 (45.647)
SSE- Full Sample	0.015070 (2.010)	0.050117 (4.600)	-0.000465 (-0.036)	0.946438 (83.061)
SSE-Sub Period1	0.021887 (1.011)	0.073325 (3.104)	-0.007735 (-0.267)	0.929503 (38.077)
SSE-Sub Period2	0.102473 (1.404)	0.046740 (1.520)	0.068928 (1.359)	0.893864 (24.779)
SSE-Sub Period3	0.027774 (2.001)	0.032853 (2.651)	-0.000366 (-0.02208)	0.949796 (65.281)
FTSE/JSE-Full Sample	0.017441 (3.772)	0.011768 (1.009)	0.128362 (6.515)	0.908406 (72.171)
FTSE/JSE-Sub Period1	0.068115 (3.062)	0.018387 (0.612)	0.143276 (3.152)	0.850920 (28.246)
FTSE/JSE-Sub Period2	0.004065 (0.545)	0.000000 (0.000001)	0.108588 (3.600)	0.943761 (41.981)
FTSE/JSE-Sub Period3	0.027774 (2.975)	0.000000 (0.000000)	0.162731 (4.238)	0.878611 (31.645)

From the table 5, the estimation results of the GJR-GARCH (1, 1) model show that the leverage effect term of the BOVESPA, MICEX, SENSEX and FTSE/ JSE is observed to be significant and SSE is insignificant in all the periods.

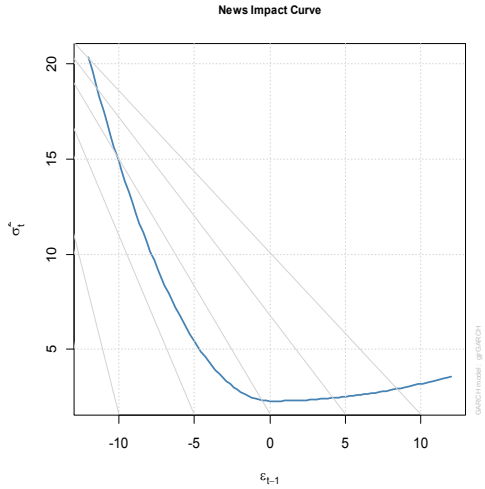
News impact curves

The news impact curve analysis is very useful in analyzing the data with asymmetries and introduced by Pagan and Schewert (1990). The curve estimates the effect of positive and negative news on volatility (Engle and Ng (1993)). On the horizontal axis the negative values represent the negative news or bad news, whereas the positive values represent the positive news or good news. The vertical axis denotes the current volatility series.

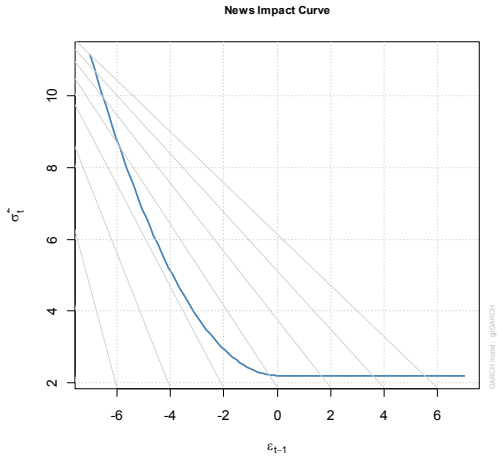
The news impact curves for the GJR-GARCH models of all the five indices for all the periods are given in the following figures (2a-2e). These results show that the four indices BOVESPA, MICEX, SENSEX and FTSE/JSE are more suitable to GJR-GARCH (1, 1) and SSE is GARCH (1, 1) models.

Figure 2a: News Impact Curves of BOVESPA

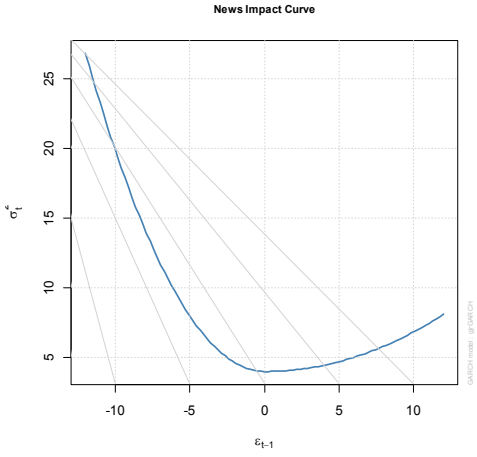
Full Sample



Sub Period1



Sub Period2



Sub period3

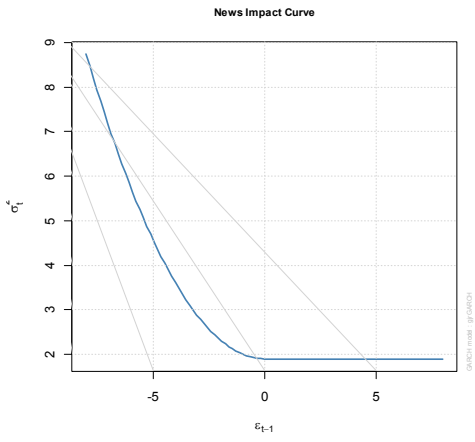
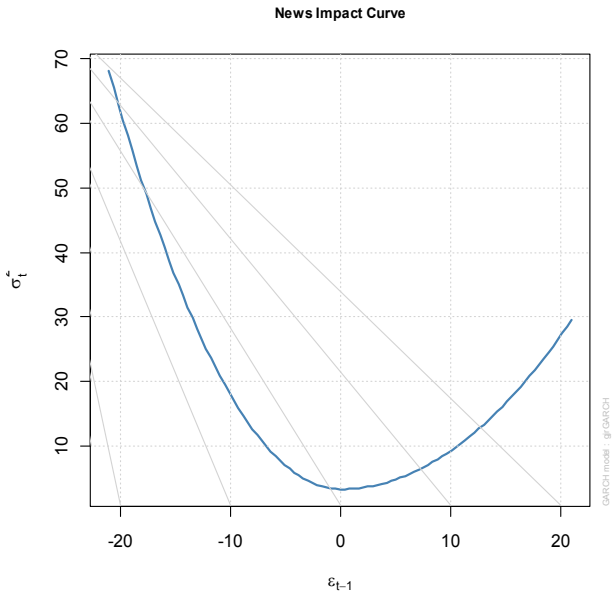
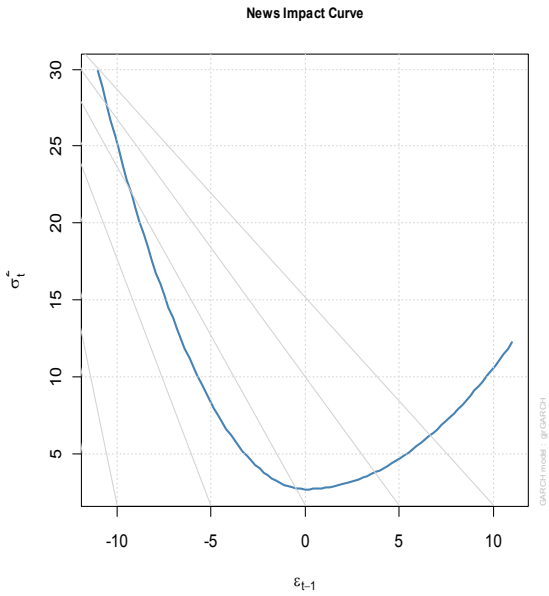


Figure 2b: News Impact Curves of MICEX

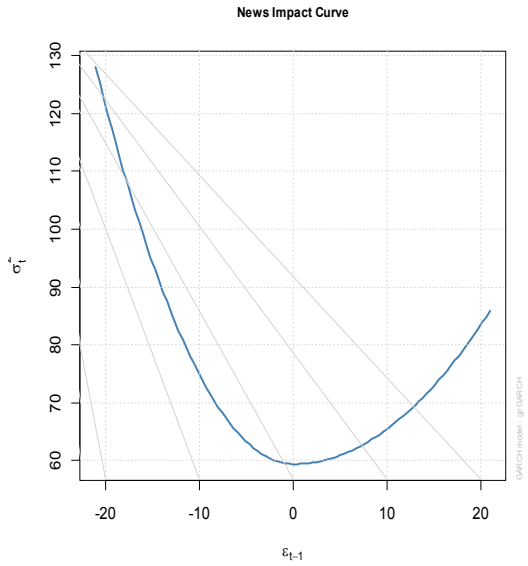
Full Sample



Sub Period1



Sub Period2



Sub Period3

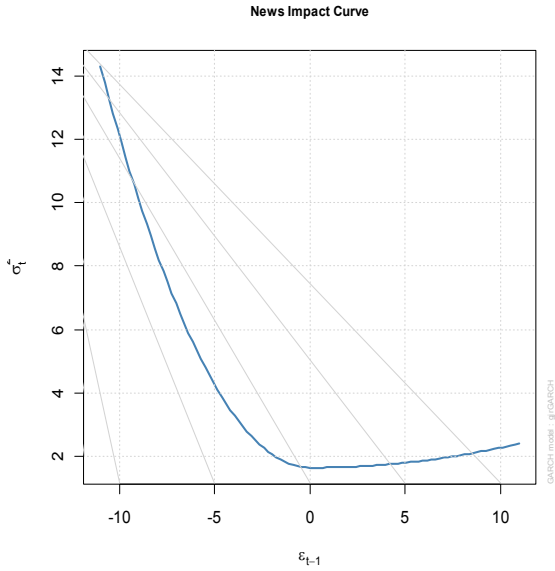
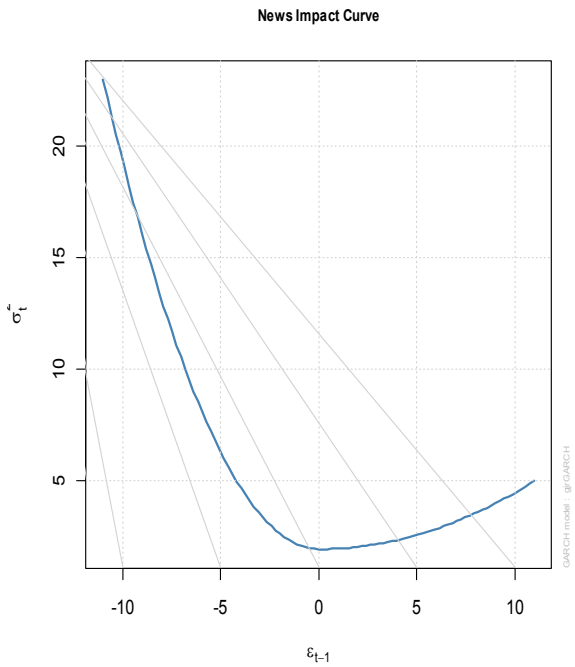
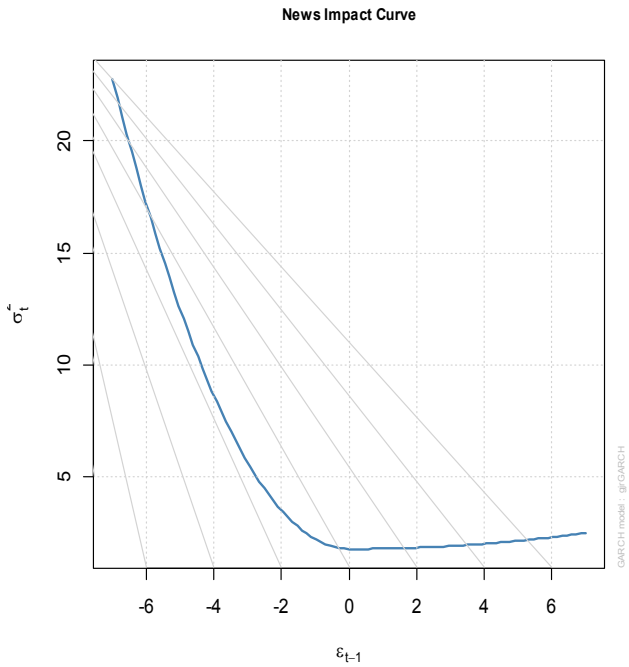


Figure 2c: News Impact Curves of SENSEX

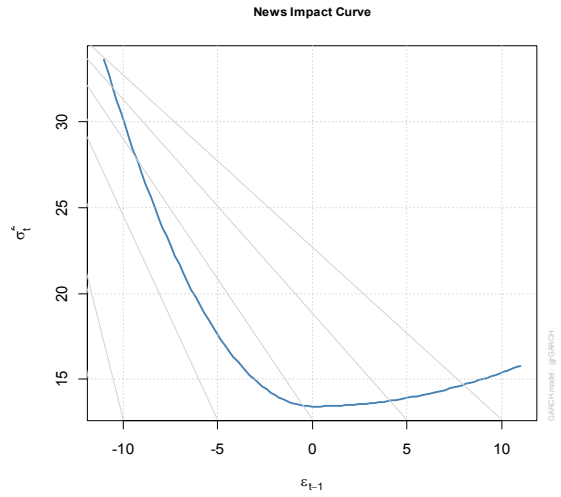
Full Sample



Sub period1



Sub Period2



Sub Period3

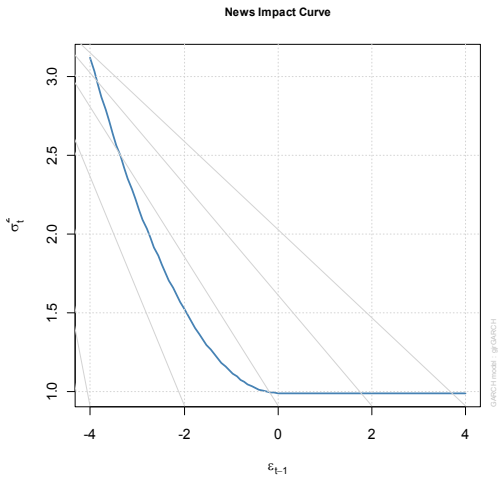
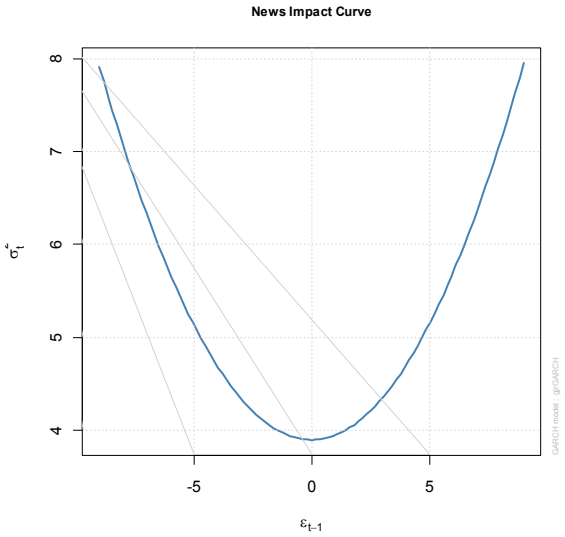
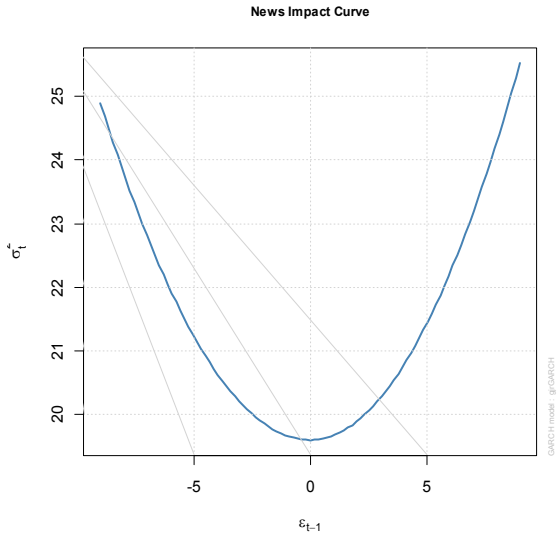


Figure 2d: News Impact Curves of SSE

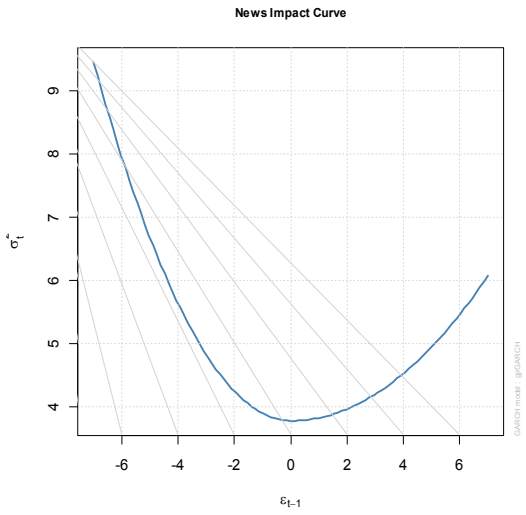
Full Sample



Sub Period1



Sub Period2



Sub Period3

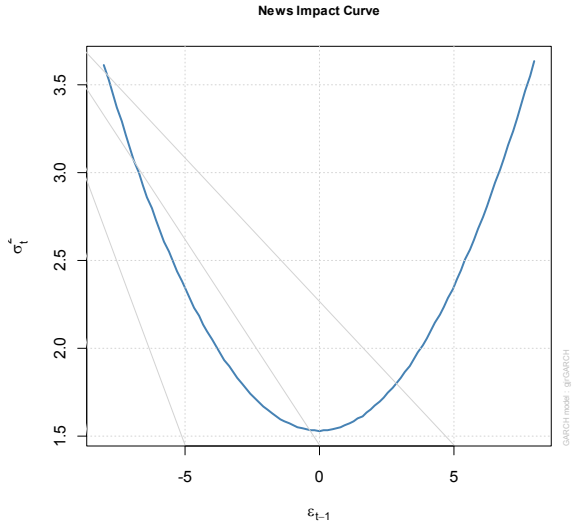
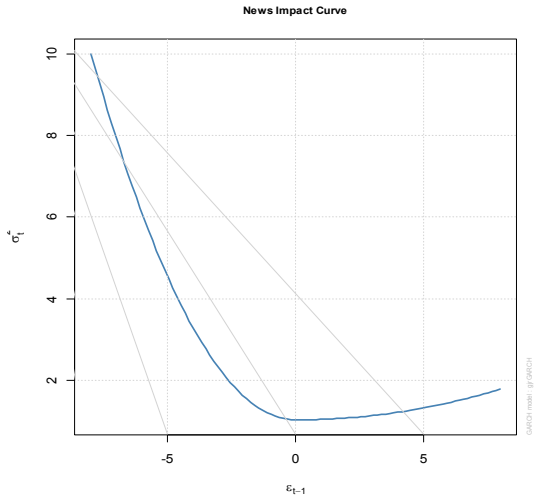
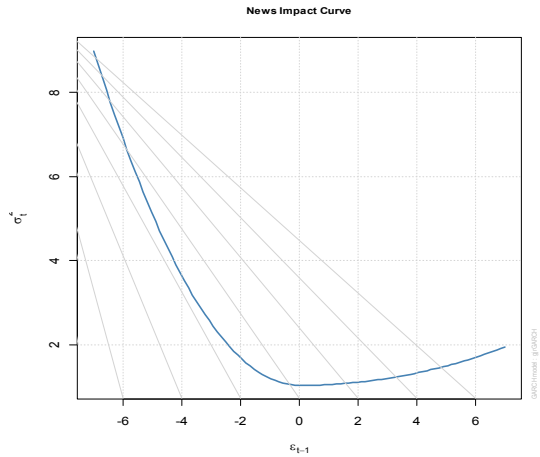


Figure 2e: News Impact Curves of FTSE/JSE

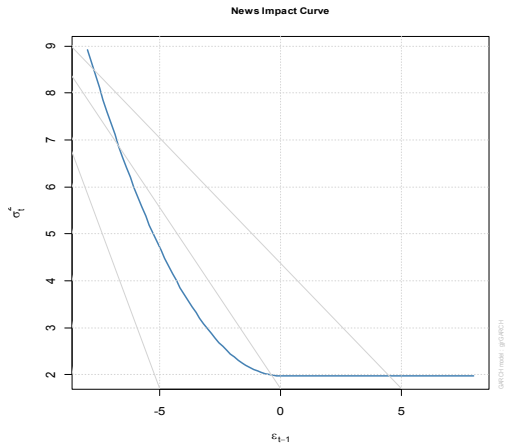
Full Sample



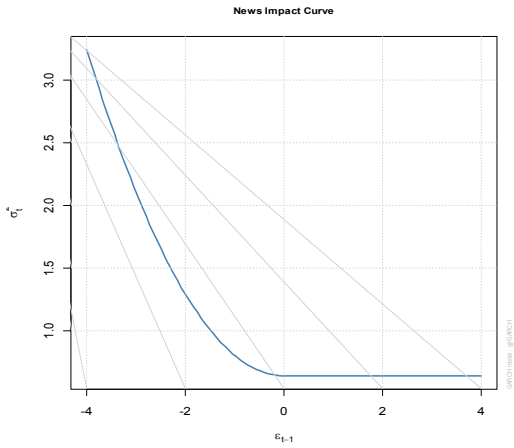
Sub Period1



Sub Period2



Sub Period3



From the figures 2a-2e, the news impact curve for the GJR-GARCH model we can see that the GJR-GARCH news impact curve is asymmetric with negative shocks having more impact on volatility than positive shocks of the same magnitude in all the indices BOVESPA, MICEX, SENSEX and FTSE/JSE except SSE. This also supported by the estimation results of section 3.3. The absence of leverage or asymmetry in case of SSE market might be due to the fact that the China market is less open and more state controlled it is insulated to any shock.

Summary & Conclusion

Due to globalization of economies, the emerging economies have attracted a lot of attention among the investors all over the world. However, it is essential to understand the behavior of the markets to have better returns for their investments. In this study the daily data of five emerging economies namely BRAZIL, RUSSIA, INDIA, CHINA and SOUTH AFRICA have been analyzed for the period 31st March 2005 to 31st March 2015. The data is further divided into

three sub periods which includes pre crisis, crisis and post crisis periods. The return series of these indices are observed and tested for the characteristics of the series such as volatility persistence, asymmetric effects in volatility and leverage effects using the popular GARCH models viz. GARCH, GJR-GARCH for these emerging stock indices. The results of this study show that the volatility is found to be highly persistent in all the five indices for all the periods except in the post crisis period of SSE. The asymmetries in volatility and leverage effect have been observed in all the indices except in SSE. This indicates that the stock markets of China are not significantly affected by the information.

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