GARCH and TGARCH Models in BRIC Economies: Prediction of Stock Market Volatility

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Volatility of returns in financial markets can be a major stumbling block for attracting investment in developing economies. In this study, the Autoregressive Integrated Moving Average (ARIMA) models and the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models are used to find out the presence of the stock market volatility on stock markets of BRIC economies. This study investigates the pattern of volatility in daily trading volume index of BRIC stock exchanges for the period 1997- 2020. The empirical evidence suggests that GARCH and TGARCH (threshold GARCH) specifications are superior to the traditional ARIMA model.

Key words: BRIC, Stock Market Volatility, GARCH, TGARCH, Prediction

1. Introduction

Stock market volatility is induced by changes in investor opportunity due to flow of new information to the market at far removed from points in time. A number of stylized facts about the volatility of financial asset prices have emerged over the years, and been studied in previous studies. Volatility clustering is defined as the well-built fluctuations in stock price which are followed by further more fluctuations, of either sign and less fluctuation tend to be followed by further less fluctuation (Mandelbrot, 1963 and Fama, 1965). The implications of such volatility clustering are volatility shocks today that will influence the expectation of volatility in future. The effect of volatility shocks depend upon with time and the volatility slowly returns to its mean level; this characteristic is termed as mean reversion.

Various studies have been well developed after the seminal work of Engle (1982) on the ARCH model and its GARCH by Bollerslev (1986) to study the characteristics of time series financial data like stock price, index level, interest rate, exchange rate, inflation rate etc. and also the characteristics of stock market volatility in developed, emerging and transition economies. It has been well recognized that while the financial time series data are non-Gaussian, auto-correlated or serially correlated and non-stationary in natures. It concludes that the volatility of such financial data possesses the characteristics of clustering, asymmetry and persistence in all the financial markets of the world. Uncertainty in the fluctuations of financial assets was first acknowledged by Mandelbrot (1963) and Fama (1965). Following the seminal work of these researchers, many researchers have found that the empirical distribution of stock returns is extensively non-normal Hsu et al. (1974); Hagerman (1978); Lau et al. (1990); Kim and Kon (1994). They found that the excess kurtosis of the stock returns. In other words, the time series of stock returns are leptokurtic, skewed and the variability of this stock returns are clustering. Some researchers viewed this as the persistency of the stock market volatility and uncertainty or risk. French et al. (1987) investigated that leverage was most likely not the sole description for the negative relation between stock returns and volatility. Engle (1993) implemented new diagnostic tests of partially non-parametric model for discovering the pragmatic association between news, volatility, and a metric for interpreting the differences among volatility models. The results also indicated that of the variance parametric models, the Glosten Jagannathan and Runkle (GJR) model was the best at parsimoniously capturing the asymmetric effect of the time series financial data. Xu (1999) comparing GARCH, EGARCH, and GJR-GARCH methods in Shanghai Stock Market and found that unexpected negative returns causes volatility increase almost equal to that of unexpected positive returns of the same degree because of no so-called leverage effect and reason was volatility is mainly caused by government policies on stock markets under the present financial system. Beakert and Wu (2000) examined the asymmetric volatility in Japanese equity market based on a multivariate GARCH-in-mean model; they tried to discriminate between the two main explanations for the asymmetry. Blair et al. (2001) presented the theoretical uncertainty of detailed analysis of the daily volatility of the S&P 100 index from 1984 to 1998 using ARCH models that incorporate leverage effects, dummy variables for the 1987 crash and aggregate measures of stock return volatility. Friedmann and Sanddorf-Kohle (2002) analyzed volatility dynamics in the Chinese stock markets by comparing the EGARCH (exponential GARCH) with the GJR GARCH model. Malmesten et al. (2004) considered the standard GARCH, the EGARCH and the AR stochastic volatility model. Rajni and Reddy (2006) discussed volatility of returns in Fiji's stock market using the ARCH models and the GARCH model to find out the presence of the stock market volatility. Thavaneswaran et al. (2006) pointed out that volatility clustering and conditional non-normality induced leptokurtosis observed in high frequency data using family of GARCH models like non-Gaussian GARCH, non-stationary and random coefficient GARCH and power GARCH. Koilakiotis et al. (2007) examined whether trading volume has any impact on GARCH and GJR- GARCH estimates for the Greek banking sector and the Greek FTSE/ASE Mid 40 stock price index for the period of

2000-2005. Haitham and Bashir (2007) empirically examined the market efficiency, asymmetric effect and time varying risk-return relationship for daily stock return of Amman Stock Exchange (ASE) using the EGARCH and threshold GARCH (TGARCH) to measure the persistent of volatility, risk –return relationship and volatility magnitude to bad and good news. Daal et al. (2007) and Chung (2009) applied asymmetric GARCH and TAR-GARCH-Jump models to capture several distinctive characteristics of the return dynamics and the strength of volatility clustering in emerging markets. Arekar and Jain (2011) have appreciably contributed on volatility in Indian stock markets during the period of recession whereas Tseng and Li (2012) introduced a quantitative method to quantify and compare volatility clustering behavior among various financial time series. A model is proposed which can imitate the stylized facts in financial markets. It is seen that researches together with India, other developing and developed economies have been taken more in comparison to rest of the countries. This chapter deals with modelling of trading volume of BRIC stock exchanges from 1997 to 2020 are utilized. The term BRIC which connotes a combination of four countries such as Brazil, Russia, India and China was first forged by Jims O' Neil in 2001, then chief economist of Goldman Sachs in a paper titled "Building Better Global Economic BRIC". Later on in 2011, South Africa was inducted to the group as the fifth nation on grounds of its strong banking sector and being the most industrialised in the African continent and hence, the acronym of BRIC was changed to BRICS thereafter. From the above two predictions, it may be inferred that the BRICS countries are becoming more powerful economic block of the world with time in terms of contribution to the World Gross Product. The BRICS share of contribution to the world economy has gone up to $19.66 trillion in 2018 as against $15.07 trillion in 2012 in nominal GDP terms while the world's total nominal gross product was $74.62 trillion and $87.51 trillion respectively in 2012 and 2018 (Statista, 2019 and 2017).

Engle (2001) investigated the efficiency of GARCH models when dealing with high frequency data. The GARCH and TGARCH models are applied to frame the model of volatility implications of trading volume of BRIC stock markets. It is studied that both non-linear GARCH and TGARCH models are the parsimonious models. However, TGARCH models were able to identify the impact of good and bad news of stock markets. The present work offers a valuable addition to the existing literature and should prove to be useful to investors as well as regulators, as this is a key index for BRIC economies.

The rest of this chapter is organized as follows. Section 2 contains a brief discussion of the methodology of the experimental analysis. Section 3 investigates empirical results and discussion of the analysis and Section 4 explains concluding remarks of the study.

2. Methodology

The results presented in this chapter are based on an analysis of the data on daily closing price of the indices of BRIC economies which are downloaded from www.finance.yahoo.com. Table 1 describes detail about the stock market data of BRIC economies whereas Table 2 shows the descriptive statistics of the daily data of these four stock markets.

Table 1 *Description of Data*

Sl. No.	Country	Type	Name of the Index	Period of Study	Total Number of Observations
1	Brazil	Emerging	Brazil's BOVESPA Stock Index (BVSP)	02/01/1997 till 13/01/2020	5699
2	Russia	Emerging	Moscow Stock Exchange (MOEX)	23/09/1997 till 15/01/2020	5581
3	India	Emerging	Bombay Stock Exchange (BSE)	01/07/1997 till 15/01/2020	5546
4	China	Emerging	Hang Seng (HSI)	02/01/1997 till 17/01/2020	5677

Source: Researcher's Distillation

Table 2 *Basic Statistics of Closing Price of the Indices of BRIC Economies*

Statistical Results	LBVSP	LMOEX	LBSE	LHSI
Mean	10.42183	6.658606	9.337274	9.776218
Median	10.76638	7.230063	9.624613	9.875163
Maximum	11.68328	8.055694	10.64430	10.40892
Minimum	8.468213	2.919391	7.863313	8.803938
Std. Dev.	0.761104	1.122359	0.846320	0.348308
Skewness	-0.501244	-1.150036	-0.252475	-0.404328
Kurtosis	1.851433	3.387031	1.602403	2.110902
Jarque-Bera	551.8985	1265.055	510.2906	341.6659
Probability	0.000000	0.000000	0.000000	0.000000
Sum	59394.01	37161.68	51784.52	55499.59
Sum Sq. Dev.	3300.731	7029.066	3971.651	688.6042
Observations	5699	5581	5546	5677

*Source: Compiled from E Views Output; *Note: LBVSP- Ln(BVSP), LMOEX- Ln(MOEX), LBSE- Ln(BSE), LHSI- Ln(HSI)*

Figure 1 shows the plotting of the daily stock closing prices of index values of Brazil (LBVSP), Russia (LMOEX), India (LBSE) and China (LHSI). For testing the presence of a unit root the augmented Dickey-Fuller (ADF) unit root tests are applied. Table 3 shows that the hypothesis of a unit root of four daily stock prices of indices cannot be rejected.

All these four indices of y_t were transformed into return R_t where $R_t = 100 \times [Ln(\frac{y_t}{y_{t-1}})]$ and y_{t-1} is the one period lag of y_t. R_t of Brazil (RBVSP), Russia(RMOEX), India (RBSE) and China (RHSI) continuously compounded daily closing returns of four trade indices. The series R_t of BRIC economies appear to less volatile at the side of periods with large increase and decrease and evidently mean reverting process with signal of volatility clustering. Figure 2 shows the plotting of the daily stock returns of four countries over the period of time. Again the daily data series of four counties are tested for the presence of a unit root. Table 3 shows that the hypothesis of a unit root is rejected for these four indices. Hence, all the returns of four indices became stationary as the above test statistics are less than the 5 per cent level of significance.

Volatility, an indication of stock market interruption, is coupled with unpredictability, uncertainty and is usually realized through time varying conditional variance of univariate data series. GARCH AND TGARCH models are applied for the estimation of trading volume volatility of the stock markets of BRIC economies. Following Bollerslev (1987) a univariate GARCH model with AR mean can be specified as:

$$R_t = a_0 + \sum_{i=1}^{s} a_i R_{t-i} + \varepsilon_t \quad (1)$$

where $\sum_{i=1}^{s} a_i < 1$, R is the continuously compounded trading volume. Unconditionally, the error term ε_t is a zero mean random shock process. The conditional distribution of ε_t follows normal distribution with $N(0, \mathrm{h_t})$, where:

$$h_t = c + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{q} \beta_i h_{t-i} \quad (2)$$

where $c > 0$, $\alpha_i, \beta_i \geq 0$ for all i, and $\sum_{i=1}^{p} \alpha_i + \sum_{i=1}^{q} \beta_i < 1$.

Most of the existing experimental studies follow the first order $(p = q = 1)$ GARCH process. This process has become the most popular GARCH model Taylor (1986). It is a valuable innovation which allows a parsimonious specification with first-order GARCH model contains three parameters. These parameters are estimated by iterative process applying maximum likelihood. A best fitted GARCH model can identify and eliminate all the dynamic and robust behaviour of the model's mean and variance. The estimated residuals of the univariate data series should be serially unautocorrelated and should not show any remaining conditional volatility. For testing the adequacy of mean and variance models, Ljung-Box (1978) Q −statistics is used. Insignificant Q −statistics for demeaned residuals indicates that the mean model is adequate. Similarly, insignificant Q −statistics for demeaned squared residuals indicates that there is no remaining GARCH effect, Sabiruazzaman et al. (2010).

A simple GARCH (1,1) model is:

$$h_t = c + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1} \quad (3)$$

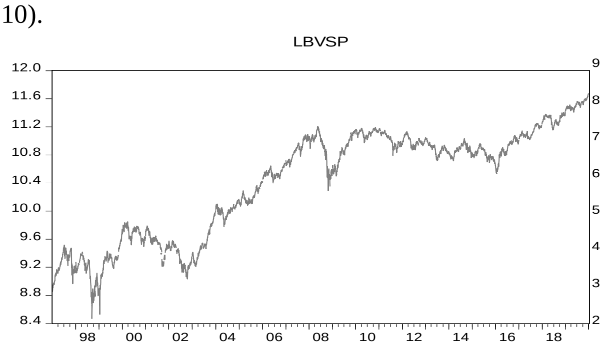
where $c > 0$, $\alpha_1, \beta_1 \geq 0$ for all i, and $\alpha_1 + \beta_1 < 1$.

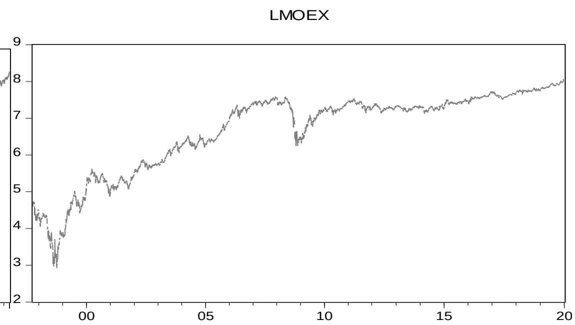
Glosten et al. (1993) developed threshold GARCH (TGARCH) model which is capable of separating out the asymmetric information. It identifies the effect of good and bad news on volatility of stock markets; Sabiruzzaman et al. (2010). Hence, TGARCH (p, q) model is:

$$h_t = \alpha_0 + \sum_{j=1}^{q} (\alpha_j + \gamma_j d_{t-j}) \varepsilon_{t-j}^2 + \sum_{i=1}^{p} \beta_i h_{t-i} \quad (4)$$

$$\text{where } d_{t-j} = \begin{cases} 1 \; if \, \varepsilon_{t-j} < 0 \\ 0 \; if \, \varepsilon_{t-j} \geq 0 \end{cases}$$

and α_j, γ_j and β_i are nonnegative parameters satisfying conditions similar to those of GARCH. From the above model, it is indicated that positive contributes $\alpha_j \varepsilon_{t-j}^2$ to h_t whereas negative news has a large impact $(\alpha_j + \gamma_j)\varepsilon_{t-j}^2$ with $\gamma_j > 0$. Some basic statistics of the transformed series and the Ljung-Box Q-statistics are given in Table 4 and Table 5 respectively, Sabiruazzaman et al. (2010).





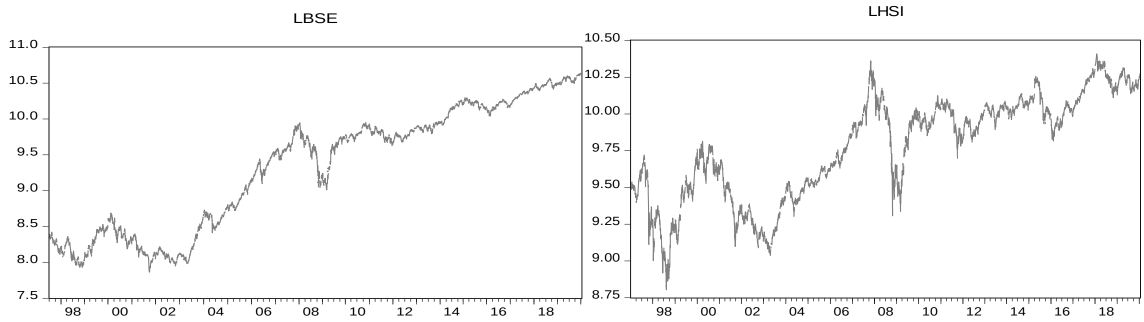


Figure 1 *Daily Stock Prices of Index Values of BRIC Economies*

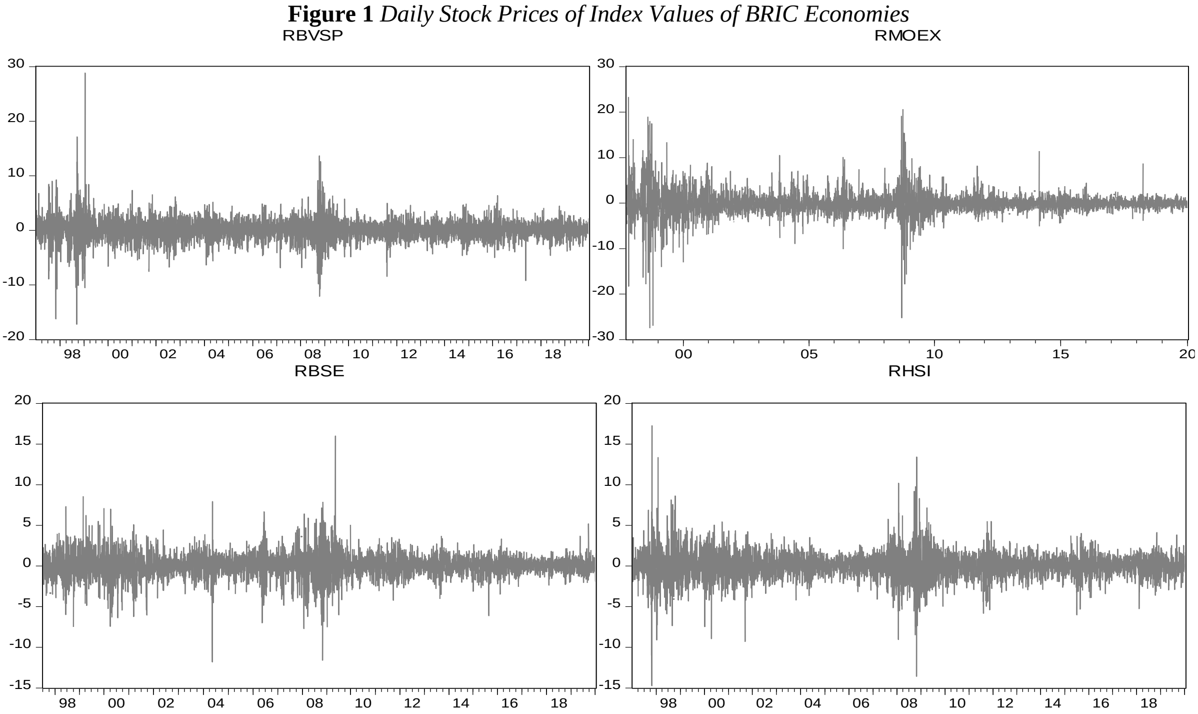


Figure 2 *Daily Stock Returns of Index Values of BRIC Economies*

Table 3 *ADF Results of Level and Return Stock Indices of BRIC Economies*

	ADF TEST RESULTS OF LEVEL DATA					
Name of the Index	ADF Test Results (constant)			ADF Test Results (constant and trend)		
	Computed Value	MacKinnon Critical Value at 5% Level	P Value	Computed Value	MacKinnon Critical Value at 5% Level	P Value
LBVSP	-1.385506	-2.861852	0.5910	-2.507133	-3.410593	0.3246
LMOEX	-1.405294	-2.861863	0.5813	-1.910876	-3.410610	0.6486
LBSE	-0.274126	-2.861866	0.9263	-2.600384	-3.410615	0.2802
LHSI	-1.537868	-2.861854	0.5144	-3.383029	-3.410596	0.0537
	ADF TEST RESULTS OF FIRST DIFFERENCE					
Name of the Index	ADF Test Results (constant)			ADF Test Results (constant and trend)		
	Computed Value	MacKinnon Critical Value at 5% Level	P Value	Computed Value	Critical Value at 5% Level	P Value
RBVSP	-74.12425	-2.861852	0.0001	-74.11943	-3.410593	0.0001
RMOEX	-68.38633	-2.861863	0.0001	-68.38456	-3.410610	0.0000
RBSE	-52.84722	-2.861866	0.0001	-52.84622	-3.410615	0.0000
RHSI	-75.02723	-2.861854	0.0001	-75.02185	-3.410596	0.0000
Note: Null Hypothesis: There is unit root. Alternative Hypothesis: There is no unit root Source: Compiled from E Views Output						

Table 4 *Descriptive Statistics of Stock Returns of BRIC Economies*

Statistical Results	RBVSP	RMOEX	RBSE	RHSI
Mean	0.049632	-0.061609	0.041043	0.013896
Median	0.093116	-0.092841	0.084158	0.054258

Maximum	28.83245	23.33561	15.98998	17.24699
Minimum	-17.20824	-27.50052	-11.80918	-14.73457
Std. Dev.	1.994257	2.476387	1.481414	1.605984
Skewness	0.296453	-0.119078	-0.096461	0.084387
Kurtosis	16.63683	21.00500	9.871092	13.33827
Jarque-Bera	44234.22	75385.01	10916.52	25283.82
Probability	0.000000	0.000000	0.000000	0.000000
Sum	282.8028	-343.7780	227.5820	78.87651
Sum Sq. Dev.	22657.32	34213.17	12166.80	14636.87
Observations	5698	5580	5545	5676

*Source: Compiled from E Views Output; *Note: RBVSP-Return (BVSP), RMOEX-Return (MOEX), RBSE- Return (BSE), RHSI- Return (HSI)*

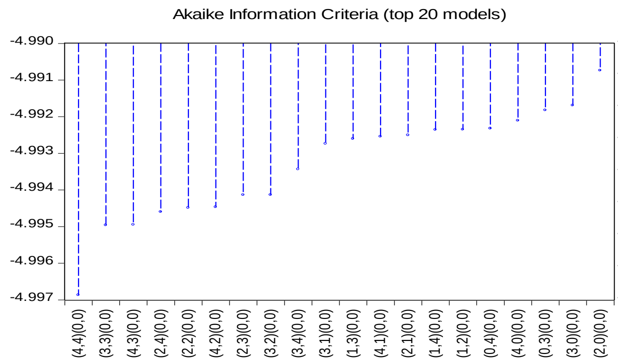
Table 5 *Ljung-Box Q-statistics of* R_t

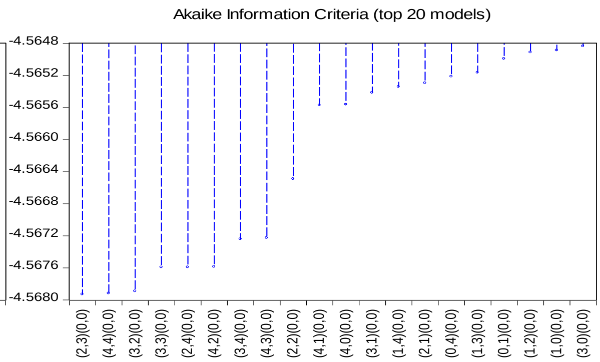
RBVSP			RMOEX			RBSE			RHSI		
Lag	Q-Statistics	p-value	Lag	Q-Statistics	p-value	Lag	Q-Statistics	p-value	Lag	Q-Statistics	p-value
4	17.522	0.002	4	53.920	0.000	4	39.452	0.000	4	19.488	0.001
8	33.672	0.000	8	62.898	0.000	8	52.731	0.000	8	26.328	0.001
12	65.781	0.000	12	74.405	0.000	12	63.760	0.000	12	29.656	0.003
16	73.369	0.000	16	91.606	0.000	16	70.334	0.000	16	39.100	0.001
20	78.428	0.000	20	114.45	0.000	20	93.302	0.000	20	42.041	0.003
24	81.326	0.000	24	119.13	0.000	24	98.625	0.000	24	45.475	0.005
28	84.729	0.000	28	124.43	0.000	28	100.61	0.000	28	52.262	0.004
32	93.607	0.000	32	148.95	0.000	32	109.45	0.000	32	68.343	0.000
36	103.30	0.000	36	157.10	0.000	36	112.90	0.000	36	74.061	0.000

Source: Compiled from E Views Output

3. Experimental Results and Discussion

At first auto-regressive (AR) models are applied in the four univariate data series to describe the mean. After considering a number of specifications, the four parsimonious ARIMA models are identified for the BRIC economies namely ARIMA (4,1,4), ARIMA (2,1,3), ARIMA (4,1,4) and ARIMA (4,1,4) models respectively. Figure 3 indicates the best model of four series through Akaike information criteria. Table 6 shows the ARIMA models of the series of BRIC economies. The models include the lagged dependent variables (p), difference term (d) and lagged error terms (q). The Ljung-Box Q-statistics for residuals and for squared residuals are given. The estimated coefficients except few in Equations (5) to (8) are highly significant at 5% level of significance. Ljung-Box-Q-statistics for demeaned residuals do not reject the null hypothesis of no autocorrelation demonstrating the residuals are following white noise process. However, the Ljung-Box-Q-statistics of the squared residuals strongly reject the null hypothesis of no autocorrelation, which is an indication of ARCH/GARCH effect of these four models. Accordingly, the parameters of the mean and the variance models are estimated of BRIC economies which are shown in Table 7. The combined estimation of AR(0) and GARCH(1,1) , AR(1) and GARCH(1,1), AR(1) and TGARCH(1,1) and AR(3) and TGARCH(1,1) models of BRIC economies respectively. All of the estimated coefficients in Equations (9) to (12) are highly significant at 5% level of significance. The Ljung-Box Q-statistics for demeaned residuals are insignificant signifying adequate mean models. The insignificant Q-statistics for demeaned squared residuals indicates for absence of GARCH effect. The residuals of these four models do not show any inadequacy in the models.





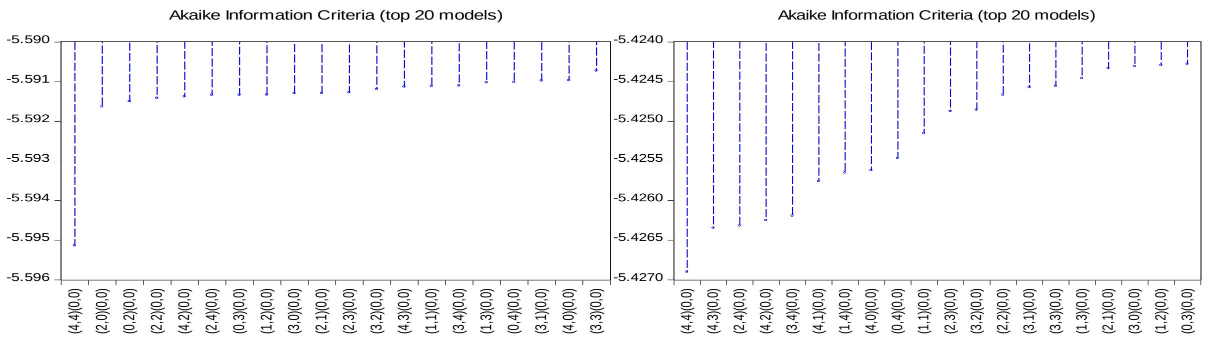


Figure 3 *Akaike Information Values of Top 20 Models of Daily Stock Returns of Index Values of BRIC Economies*

Table 6 *ARIMA Models of Daily Stock Returns of Four Indices of BRIC Economies*

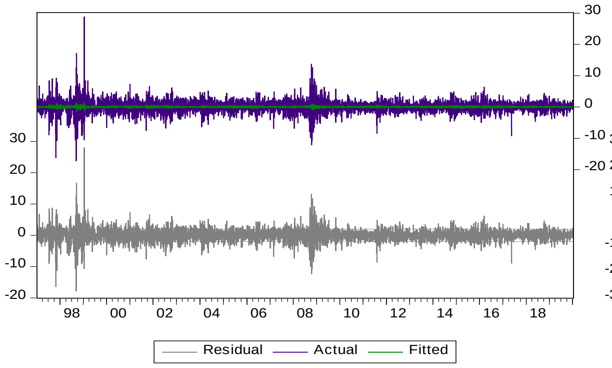
Economy	ARIMA(p,d,q)	ARIMA Model
Brazil	(4,1,4)	$\hat{R}_t = 0.04888 - 0.3543\hat{R}_{t-1} + 0.75881\hat{R}_{t-2} + 0.11991\hat{R}_{t-3} - 0.71881\hat{R}_{t-4} + 0.37509\hat{\varepsilon}_{t-1} - 0.77896\hat{\varepsilon}_{t-2} - 0.17843\hat{\varepsilon}_{t-3} + 0.68527\hat{\varepsilon}_{t-4}$ (5)
	$t-ratio$	(2.01118) (-3.46076) (7.18415) (1.38585) (-7.78648) (3.47536) (-7.11544) (-1.93414) (6.85974)
	$p-value$	(0.0444) (0.0005) (0.0000) (0.1658) (0.0000) (0.0005) (0.0000) (0.0531) (0.0000)
	Ljung Box Q-statistics for residuals	Q(9)=8.0522(0.005), Q(12)=24.398(0.000), Q(15)=33.337(0.000)
	Ljung Box Q-statistics for squared residuals	Q(9)=1294.7(0.000), Q(12)=1541.2(0.000), Q(15)=1688.5(0.000)
	ARCH effect	F-value = 244.5567 (p-value of the F-statistic = 0.0000)
Russia	(2,1,3)	$\hat{R}_t = -0.06211 + 1.30262\hat{R}_{t-1} - 0.92811\hat{R}_{t-2} - 1.21717\hat{\varepsilon}_{t-1} + 0.81947\hat{\varepsilon}_{t-2} + 0.59333\hat{\varepsilon}_{t-3}$ (6)
	$t-ratio$	(-1.78161) (43.55893) (-32.81461) (-36.92502) (25.72101) (4.02867)
	$p-value$	(0.0749) (0.0000) (0.0000) (0.0000) (0.0000) (0.0001)
	Ljung Box Q-statistics for residuals	Q(6)=1.4002(0.237), Q(10)=8.1068(0.150), Q(15)=19.033(0.040)
	Ljung Box Q-statistics for squared residuals	Q(6)=1508.2(0.000), Q(10)=1882.7(0.000), Q(15)=2640.8(0.000)
	ARCH effect	F-value = 645.1568 (p-value of the F-statistic = 0.0000)
India	(4,1,4)	$\hat{R}_t = 0.04093 + 1.13169\hat{R}_{t-1} - 1.11164\hat{R}_{t-2} + 0.38163\hat{R}_{t-3} - 0.41991\hat{R}_{t-4} - 1.05724\hat{\varepsilon}_{t-1} + 0.99206\hat{\varepsilon}_{t-2} - 0.26608\hat{\varepsilon}_{t-3} + 0.37518\hat{\varepsilon}_{t-4}$ (7)
	$t-ratio$	(2.0176) (4.9949) (-4.26932) (1.85462) (-2.9457) (-4.61210) (4.00607) (-1.35926) (2.46375)
	$p-value$	(0.0437) (0.0000) (0.0000) (0.0637) (0.0032) (0.0000) (0.0001) (0.1741) (0.0138)
	Ljung Box Q-statistics for residuals	Q(9)=4.1892(0.041), Q(12)=9.4810(0.050), Q(15)=20.257(0.005)
	Ljung Box Q-statistics for squared residuals	Q(9)=1454.0(0.000), Q(12)=1765.3(0.000), Q(15)=2015.1(0.000)
	ARCH effect	F-value = 272.8997 (p-value of the F-statistic = 0.0000)
China	(4,1,4)	$\hat{R}_t = 0.01357 + 0.10032\hat{R}_{t-1} - 0.44308\hat{R}_{t-2} - 0.355555\hat{R}_{t-3} - 0.539994\hat{R}_{t-4} - 0.09506\hat{\varepsilon}_{t-1} + 0.41582\hat{\varepsilon}_{t-2} + 0.39428\hat{\varepsilon}_{t-3} + 0.49381\hat{\varepsilon}_{t-4}$ (8)
	$t-ratio$	(0.64609) (0.56706) (-3.63182) (-2.99596) (-3.35435) (-0.52261) (3.40213) (3.30506) (2.95529)
	$p-value$	(0.5182) (0.5707) (0.0003) (0.0027) (0.0008) (0.6013) (0.0007) (0.0010) (0.0031)
	Ljung Box Q-statistics for residuals	Q(9)=3.4949(0.062), Q(12)=6.2154(0.184), Q(15)=12.906(0.074)
	Ljung Box Q-statistics for squared residuals	Q(9)=2831.3(0.000), Q(12)=3277.3(0.000), Q(15)=3647.8(0.000)
	ARCH effect	F-value = 998.8744 (p-value of the F-statistic = 0.0000)

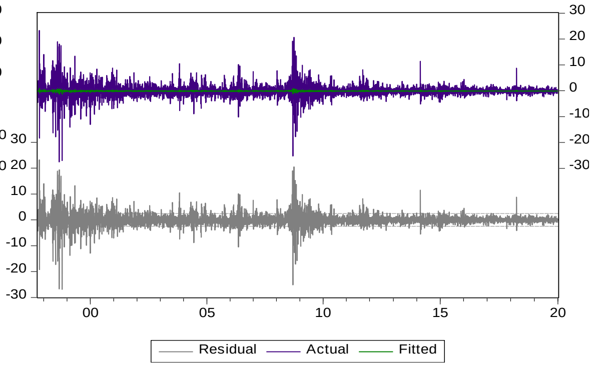
Source: Compiled from E Views Output

Table 7 *Parsimonious GARCH Models of Daily Stock Returns of Four Indices of BRIC Economies*

Economy	Model	AR and GARCH Model
Brazil	AR(0)	$\hat{R}_t = 0.084763$ (9)
	$t - ratio$	(4.09675)
	$p - value$	(0.0000)
	GARCH(1,1)	$\hat{h}_t = 0.069357 + 0.087422\hat{\varepsilon}^2{}_{t-1} + 0.893438\hat{h}_{t-1}$
	$t - ratio$	(8.06743) (18.8457) (147.1811)
	$p - value$	(0.0000) (0.0000) (0.0000)
	Ljung Box Q-statistics for residuals	Q(9) = 6.8325(0.655), Q(12) = 17.710(0.125), Q(15) = 22.578(0.094) Q(20) = 29.605(0.077) Q(25)=33.8(0.112)
	Ljung Box Q-statistics for squared residuals	Q(9)=21.385(0.011), Q(12) = 23.421(0.024), Q(15) = 24.949(0.051) Q(20) = 33.607(0.029 Q(25)=39.188(0.035)
	ARCH test	F-value = 0.103391 (p-value of the F-statistic = 0.7478)
	Conditional volatility	1.9943
Russia	AR(1)	$\hat{R}_t = -0.098957 + 0.04392\hat{R}_{t-1}$ (10)
	$t - ratio$	(-5.593641) (3.330279)
	$p - value$	(0.0000) (0.0009)
	GARCH(1,1)	$\hat{h}_t = 0.039147 + 0.113822\hat{\varepsilon}^2{}_{t-1} + 0.884158\hat{h}_{t-1}$
	$t - ratio$	(14.04272) (27.19910) (223.7322)
	$p - value$	(0.0000) (0.0000) (0.0000)
	Ljung Box Q-statistics for residuals	Q(9)=11.013(0.201), Q(12) = 13.005(0.293), Q(15) = 13.171(0.513 Q(20) = 17.815(0.535) Q(25)=22.397(0.556)
	Ljung Box Q-statistics for squared residuals	Q(9)=4.0108(0.911), Q(12)= 4.6493(0.969), Q(15) = 5.5559(0.986) Q(20) = 6.6075(0.998) Q(25)=9.3606(0.998)
	ARCH test	F-value = 0.30973 (p-value of the F-statistic = 0.5779)
	Conditional volatility	2.4766
India	AR(1)	$\hat{R}_t = 0.055116 + 0.08954\hat{R}_{t-1}$ (11)
	$t - ratio$	(3.640898) (6.067335)
	$p - value$	(0.0003) (0.0000)
	TGARCH(1,1)	$\hat{h}_t = 0.023173 + (0.042741{+}0.104093d_{t-1})\hat{\varepsilon}^2{}_{t-1} + 0.89729\hat{h}_{t-1}$
	$t - ratio$	(8.80222) (9.08974) (12.19796) (183.5689)
	$p - value$	(0.0000) (0.0000) (0.0000) (0.0000)
	Ljung Box Q-statistics for residuals	Q(9) =24.77(0.002), Q(12) = 26.066(0.006), Q(15) = 33.164(0.003) Q(20) =44.663(0.001) Q(25)=46.072(0.004)
	Ljung Box Q-statistics for squared residuals	Q(9) =4.8769(0.845), Q(12) =8.6207(0.735), Q(15) =10.669(0.776) Q(20) = 13.609(0.850) Q(25)=18.702(0.811)
	ARCH test	F-value = 0.97063 (p-value of the F-statistic = 0.3246)
	Conditional volatility	1.4815
China	AR(3)	$\hat{R}_t = 0.040564\hat{R}_{t-3}$ (12)
	$t - ratio$	(3.06981)
	$p - value$	(0.0021)
	TGARCH(1,1)	$\hat{h}_t = 0.02318 + (0.02171{+}0.08239d_{t-1})\hat{\varepsilon}^2{}_{t-1} + 0.92582\hat{h}_{t-1}$
	$t - ratio$	(8.64561) (5.0376) (12.3234) (184.0759)
	$p - value$	(0.0000) (0.0000) (0.0000) (0.0000)
	Ljung Box Q-statistics for residuals	Q(9) = 23.202(0.003), Q(12) = 26.467(0.006), Q(15) = 32.281(0.004) Q(20) = 34.831(0.015) Q(25)=41.23(0.016)
	Ljung Box Q-statistics for squared residuals	Q(9) = 13.918(0.125), Q(12) = 14.128(0.293), Q(15) = 16.659(0.340) Q(20) = 19.403(0.496) Q(25)=22.982(0.579)
	ARCH test	F-value = 3.82439 (p-value of the F-statistic = 0.0506)
	Conditional volatility	1.6063

Source: Compiled from E Views Output





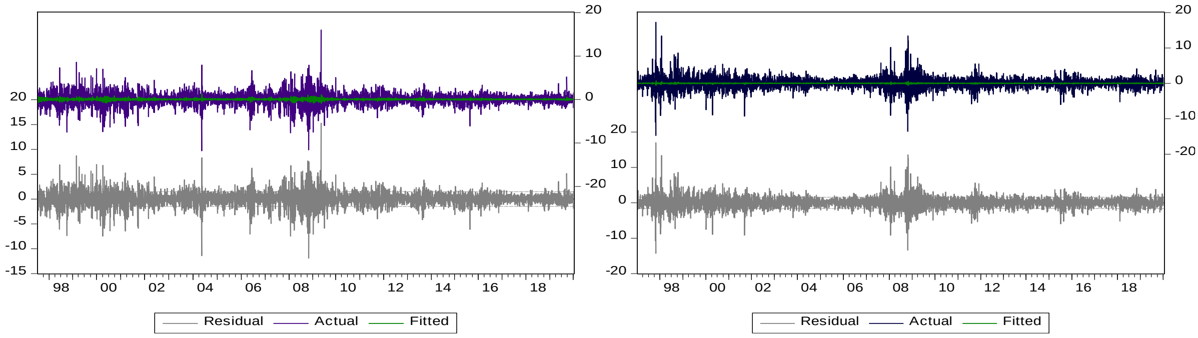


Figure 4 *Residual, Actual and Fitted Values of Daily Stock Returns of Index Values of BRIC Economies*

Figure 4 shows the residual, actual and fitted values of daily stock returns of index values of BRIC economies. The bands of the estimated conditional variance track the observed heteroskedasticity in the series of daily changes of the four indices are quite well. This is useful for quantifying the time-varying volatility and the resulting risk for investors holding stocks summarized by the index. Furthermore, these GARCH models may also be used to produce forecast intervals whose widths depend on the volatility of the most recent periods. Figure 5 and Figure 6 show the estimated values of conditional variance of daily stock returns of index values of BRIC economies with and without bands respectively. Table 8 shows the performance evaluation using RMSE, MAE, Theil inequality coefficient and SMAPE in final GARCH models of daily stock returns of index values of BRIC economies. From this evaluation it is concluded that the present models are the best to give the optimum results of estimation of parameters.

Table 8 *Performance Evaluation of GARCH Models on Four Time Series Data Sets*

Information	Brazil	Russia	India	China
No. of observation	5698	5580	5544	5673
RMSE	1.9943	2.4694	1.4774	1.6052
MAE	1.3927	1.5184	1.0302	1.0838
Theil Inequality Coefficient	0.9591	0.9414	0.9091	0.9604
Symmetric MAPE	175.9010	172.2400	170.1697	184.4803

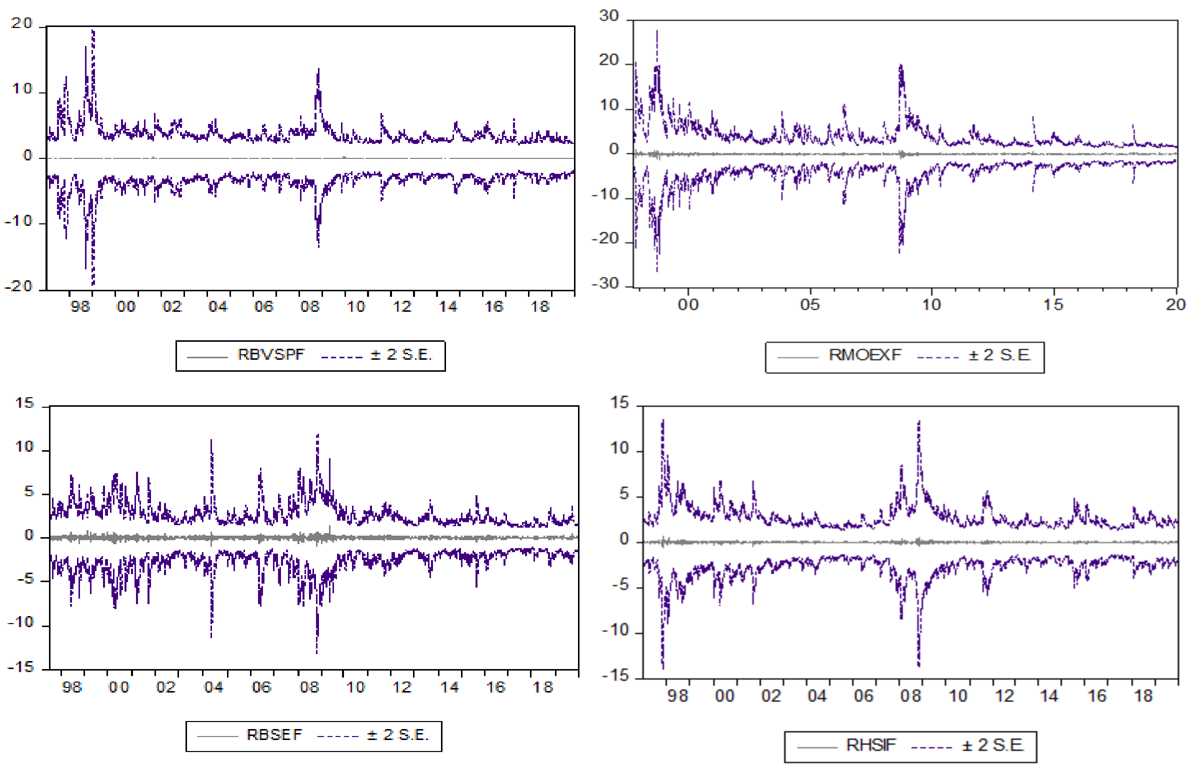


Figure 5 *Estimating Conditional Variance (with Bands) of Daily Stock Returns of Index Values of BRIC Economies*

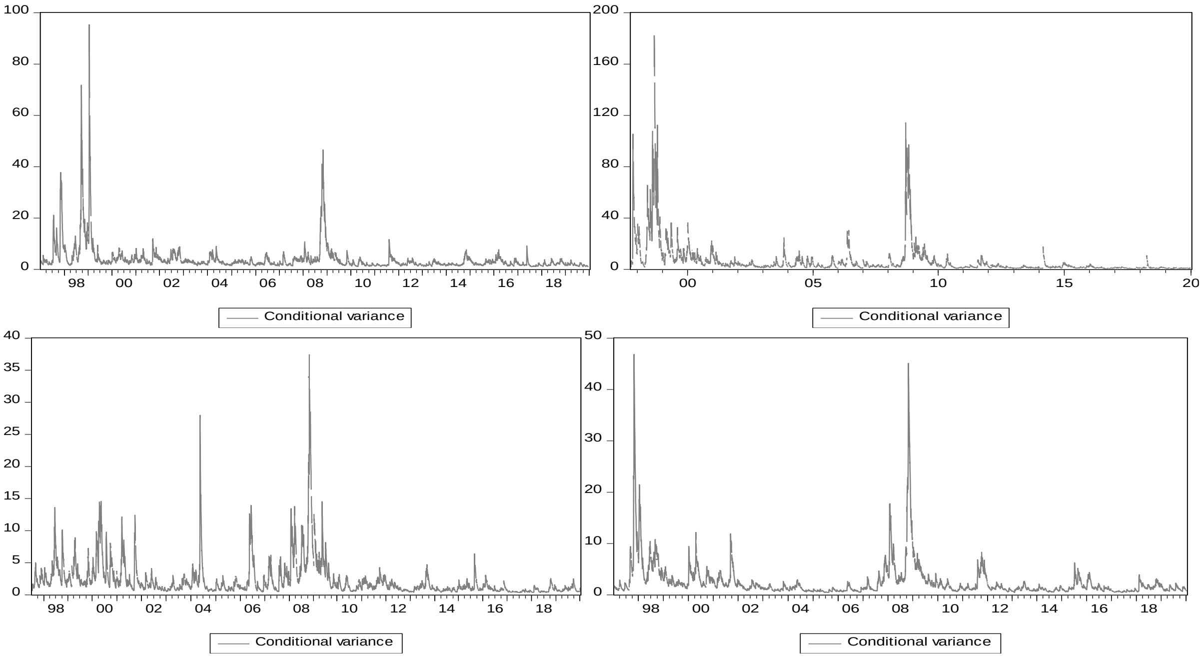


Figure 6 *Estimated Values of Conditional Variance of Daily Stock Returns of Index Values of BRIC Economies*

4. Summary and Conclusions

This chapter is studied the existence of volatility of trading volume of stock exchanges for BRIC countries. To study the volatility of these four stock markets GARCH as well as threshold GARCH (TGARCH) specifications are applied. It is found that both GARCH and threshold GARCH models fit the daily data well. However, TGARCH model is able to identify the impact of good and bad news in stock markets. Experimentally it is also shown that GARCH and TGARCH specifications are more appropriate for modelling volatile volume of trade indices of BRIC economies to avoid ARCH effect where the application of traditional ARIMA model may provide poor information on the stock market structure.

5. References

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