EXPLORING THE STOCK MARKET VOLATILITY WITH BRIC COUNTRIES - AN EMPIRICAL INVESTIGATION

P. Hemavathy [*], S. Gurusamy [**]

chennaihema@rediffmail.com

ABSTRACT

Stock market is widely considered as a major indicator to imitate investor's outlook of futuristic economic conditions. Investors in the BRIC countries have found out the hard-hitting line of attack that economic development may not convert into stock market gains, and numerous analysts criticize problems with corporate governance in Russian and Chinese markets. Volatility in equity market has happened to be an issue of reciprocated concern for investors, regulators and brokers. It is mainly understood that the stock price volatility is originated exclusively by the haphazard influx of new information connecting to the expected returns from the stock. The stock markets functioning in BRIC countries have had its reasonable share in the global financial crisis provoked by unnecessary speculation resulting in extreme volatility. Indubitably, the investor's buoyancy has been eroded by excessive volatility of Stock Markets in BRIC nations. The volatile stock market is a severe concern for policy makers since the stock market fluxes creates improbability and thus unfavorably has an effect on economic growth. This study aims to develop and examine the conditional volatility models in an attempt to confine the prominent features of volatility in stock markets in BRIC countries. This empirical study is focused on BRIC emerging markets. The study is based on secondary data acquired from Bloomberg database. The researcher have collected daily closing stock prices from its respective exchange ie, (IBOVESPA) for Brazil, (RTSI) for Russia, NSE (S&P CNX NIFTY) for India, (CSI300) for China. The researcher undertakes the popular econometric technique such as GARCH model to study the behavior of volatility of Stock markets in BRIC Countries. Results reveal that China reflects high degree of volatility of series returns among the BRIC countries. This long-lasting volatility in the stock market has been disappointing issue for the retail investors to invest in equity markets and boosted the obsession towards bullion industry in china. The researcher concludes that higher volatility is both gesture and a vehicle of uncertainty. Credit rating agencies act as driver of the stock market volatility. Credit rating agencies play an significant part in providing one source of information that aids accuracy and market capability, thereby plummeting the imbalance of information among the stock market investors.

Keywords : Generalized Autoregressive Conditional Heterokadascity, Stock Market, Volatility, Equity investors, Credit rating agencies.

INTRODUCTION

In 2001, Former Goldman Sachs economist Jim O'Neill had coined a new acronym the "BRIC"- family of Brazil, Russia, India and China. BRIC nation's stock market indices moved up progressively more, the equity investors were so ecstatic to sing and dance with anticipation when BRIC was formed. In the wake of the financial

** UGC-SRF, ** Professor and Head, Department of Commerce, University of Madras, Chennai (Tamil Nadu)*

market turmoil and loss of equity values across the globe, investor's inclination seems to be flustered and dejected. Stock market is widely considered as a major indicator to imitate investor's outlook of futuristic economic conditions. Investors in the BRIC countries have found out the hard-hitting line of attack that economic development may not convert into stock market gains, and numerous analysts criticize problems with corporate governance in Russian and Chinese markets. (Poon, S.H., and Granger, C. 2003) It is crucial to identify the model of stock market volatility in BRIC countries which is time-varying, demanding and predictable. This in turn enables to devise effective hedging strategies and facilitates to diversify international portfolio. (Pandey, A. 2005) In recent times, Volatility in equity market has happened to be an issue of reciprocated concern for investors, regulators and brokers. It is mainly understood that the stock price volatility is originated exclusively by the haphazard influx of new information connecting to the expected returns from the stock. Others aspect to act as the source of volatility to trading. Costs of trading in an exchange have a significant bearing on the capital market efficiency. Research suggests that volatility is far larger during trading hours than when the exchange is closed (Fama, 1965; French, 1980). The precision and the efficacy of a volatility forecast are of enormous significance in capital markets. Financial market participants give greater significance to volatility as it is used as an effective risk measurement tool. Stock return volatility hinders economic performance through consumer spending. Peripatetic stock prices and their volatility, which have now become widespread features of securities markets, add to the concern. Moreover the extreme volatility could break off the smooth functioning of the financial system and lead to structural and regulatory changes. Stock price Volatility negatively affects individual earnings and economic strength. It creates ambiance of improbability and thus it obstructs productive investment. There exists reasonably strong literature supporting the applicability of the GARCH models to predict volatility. Andersen and Bollerslev (1998), Corhay and Rad (1994), Brooks (1998), Pagan and Schwert (1990), MadhusudanKarmakar (2005) asserts that GARCH family of models provides the precise forecasts. The study reports an confirmation of time varying volatility, which demonstrates clustering, high persistence and certainty and responds asymmetrically for positive and negative shocks.

REVIEW OF LITERATURE

Trivedi et.al (2013) estimate the volatility of the BRIC emerging stock markets, namely Brazil, Russia, India and China based on their major stock indices. The researchers employ econometric approach includes GARCH model which is performed in order to capture asymmetric volatility clustering and leptokurtosis. Results highlight that open end security markets follow focus strategy of speculative investing rather than directions of risk management.

Ruchika Gahlot, Saroj Kumar Datta, (2012) examine the impact of the future of trading on volatility as well as the efficiency of the stock market of BRIC (Brazil, Russia, India and China) countries. The researchers uses closing prices of IBrx-50 for Brazil, RTSI for Russia, Nifty for India and CSI300 for China to represent the stock market of BRIC countries. The Run and ACF tests are used to see impact on market efficiency. GARCH M model is used to see the impact on volatility and day-of-the week effect. Results reveal that GARCH M indicates that future trading led to reduction in the volatility of the Indian stock market.

Madhusudan Karmakar (2005) examined the conditional volatility models in an attempt to capture the salient features of Indian stock market volatility. The study also investigates whether there is any leverage effect in Indian companies. The estimation of volatility is undertaken at the macro level on two major market indicies namely S&P CNX Nifty and BSE Sensex. Regression based efficiency test has also been performed. The author observed that the GARCH (1,1) model provides reasonably good forecasts for market volatility. Results reveal that the conditional volatility of market return series from January 1991 to June 2003 shows a clear evidence of volatility shifting over the period where violent changes in share prices cluster around the boom 1992.

Jun Yu (2002) evaluates the performance of nine alternative models for predicting stock price volitity using daily New Zealand data. The author develops competing models which contain both simple models such as the random walk and a stochastic volatility models. Results reveal that the stochastic volatility models provide the best performance among other models. The author highlights that the performance of the GARCH (3,2) model, the best model within the ARCH family is sensitive to the choice of assessment measures.

RESEARCH METHODOLOGY

Statement of Problem

The stock markets functioning in BRIC countries have had its reasonable share in the global financial crisis provoked by unnecessary speculation resulting in extreme volatility. Indubitably, the investor's buoyancy has been eroded by excessive volatility of Stock Markets in BRIC nations. The volatile stock market is a severe concern for policy makers since the stock market fluxes creates improbability and thus unfavorably has an effect on economic growth.

Objective of the study

To develop and examine the conditional volatility model in an attempt to confine the prominent features of volatility in stock markets in BRIC countries

Source of data

This empirical study is focused on BRIC emerging markets. The study is based on secondary data acquired from Bloomberg database. The researcher have collected daily closing stock prices from its respective exchange ie, (IBOVESPA) for Brazil, (RTSI) for Russia, NSE (S&P CNX NIFTY) for India, (CSI300) for China.

Research Design

Data time lag is from first transaction day of 1996 to 31st August 2014. "Eviews 7" Data Analysis and Econometric Software package program have been used for coordinating the data and undertaking popular econometric techniques GARCH models to study the behavior of volatility of Stock markets in BRIC Countries. The sample financial time series collected from 1st April 1996 to 31st August 2014 is the daily closing index prices. It was investigated that unit root problem in all series and hence the financial series have been transformed. The continuously compounded daily returns are calculated using the log difference of daily closing prices of select indices.

$$Rt = h\ (P_t / P_{t-1})$$
$$= h\ (P_t) - h\ (P_{t-1})$$

Where Rt represents daily returns of indices at the time of t and Pt, Pt-1 represents the daily prices of stock at two successive days, t-1 and t respectively.

MODELING THE VOLATILITY

In this section , the researcher present the most appropriate academic research on ARCH and GARCH models which are popular based econometric models for research application. ARCH model was pioneered by Engle (1982) in his study "Autoregressive Conditional Heteroscedasticity with estimates of the Variance of United Kingdom Inflation" as the initial recognized model which seemed to confine the occurrence of changing variance in time series data. It is the most extensively utilized discrete time model for analysis of financial data. The model formulation is given below:

$$\varepsilon_t = v_t\sqrt{\alpha + \sum_{i=1}^{q}\alpha_i + \varepsilon_{t-i}^{\ 2}} \quad \text{Where } v_t \sim \text{IID } (0, 1)$$

$$\sigma_t^{\ 2} = \alpha_0 + \alpha_1\varepsilon^2_{\ t-1} + \alpha_2\varepsilon^2_{\ t-2} + \ldots\ldots + \alpha_q\varepsilon^2_{\ t-q}$$

Where $\sigma^2_{\ t}$ the variance at time t is, $\varepsilon^2_{\ t}$ is the squared residual at time t, and q is the number of lags. The effect of a return shock i period ago ($I \leq q$) on current volatility is governed by the parameter ?. In an ARCH model, old news arrived at the market more than q period ago has no effect at all on current volatility. Bollerslev (1986) extended the basic ARCH model by introducing the GARCH model (Generalized Autoregressive Conditional Heteroscedasticity) which has proven to be quite useful in empirical work. The GARCH model essentially generalizes the purely autoregressive moving average model. He suggested that the conditional variance function be specified as follows:

$Y_t = X_t\beta + \varepsilon_t$ is the mean equation.

Where Y_t is the stock return, X_t is the exogenous variables or belonging to the set of information (Y_t-1), β is a fixed parameter vector and conditional variance is,

$$h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}{}^2 + \sum_{i=1}^{p} \beta_i h_{t-i}$$

Where, $\alpha_0 > 0$, α_1, α_2,............ $\alpha_q > 0$ and β_1, β_2, β_3,........., $\beta_p \geq 0$

The GARCH (p, q) above defined as stationary when $(\alpha_1 + \alpha_2 + \ldots\ldots + \alpha_q) + (\beta_1 + \beta_2 + \ldots\ldots + \beta_p) < 1$.

EMPIRICAL RESULTS AND DISCUSSION

In this section the researcher discusses about the Normality of the daily closing stock returns for the BRIC countries, stock market volatility estimates, Diagnostics testing for Volatility Clustering, Heteroscedasticity test, GARCH Model Fitting, Determination of goodness of fit for GARCH model, Diagnostics testing for the GARCH Model, Volatility Shifting, Stock Market Volatility forecasting evaluation measures using root mean square error (RMSE), mean absolute percentage error (MAPE) and mean absolute error (MAE), Theil Inequality co-efficient of the BRIC Countries stock market indices namely of IBrx-50 for Brazil, RTSI for Russia, S&P Nifty for India and CSI300 for China.

Augmented Dickey- Fuller (ADF) test

Generally all time series has unit root problems and it must be filtered and allowed for GARCH processes. Augmented Dickey-Fuller (ADF) stationary test has been employed to four market return series namely IBrx-50 for Brazil, RTSI for Russia and CSI300 for China NSE (S&P CNX NIFTY) for India. Unit Root Test is used to test whether the time series are stationary or not. It has produced higher negative value than its critical value at 1%, 5% and 10% level which allows series for GARCH and proves no unit root problems.

Descriptive Statistics for the Normality

Table 1 (Appendix) exhibits the normality of the GARCH(1,1) estimation by revealing the details pertaining to descriptive statistics of the daily closing return series of Brazil (IBOVESPA), Russia (RTSI), India (S&P NIFTY), China (CSI300). There exists normality in the daily closing return series of IBOVESPA, RTSI, S&P NIFTY, CSI300.

Brazil (IBOVESPA): The maximum return index is 5.471292, and minimum is -5.476607 which has produced high degree of standard deviation close to 1 (0.999198) with regard to 4618 observations. There is exist a positive mean for the daily closing returns series. There exists negative skewness (-0.278726) which represents an asymmetric tail which exceeds towards negative. The returns on the portfolio of the daily closing index of IBOVESPA are more or less normally distributed. The stock returns exhibits non-normality. If the returns are normally distributed, then coefficients of skewness and excess kurtosis should be equal to zero. The skewness (-0.278726) and kurtosis (4.261334) indicates that there exist normality in the daily closing return series of IBOVESPA.

Russia (RTSI): The maximum return index is 4.961839, and minimum is -9.506609 which has produced high degree of standard deviation close to 1 (0.999941) with regard to 4186 observations. There exist negative skewness (-0.438555) which represents an asymmetric tail which exceeds towards negative. The returns on the portfolio of the daily closing index of RTSI are more or less normally distributed. The stock returns exhibits non-normality. If the returns are normally distributed, then coefficients of skewness and excess kurtosis should be equal to zero. The skewness (-0.438555) and kurtosis (6.825759) indicates that there exist normality in the daily closing return series of RTSI.

India (S&P NIFTY): The maximum return index is 7.690612, and minimum is -6.670432, which has produced high degree of standard deviation close to 1 (0.999615) with regard to 4656 observations. There exists negative skewness (-0.250807) which represents an asymmetric tail which exceeds towards negative. The returns on the portfolio of the daily closing index of S&P NIFTY are more or less normally distributed. The stock returns exhibits non-normality. If the returns are normally distributed, then coefficients of skewness and excess kurtosis should be equal to zero. The skewness (-0.250807) and kurtosis (5.709933) indicates that there exist normality in the daily closing return series of RTSI.

China (CSI300): The maximum return index is 5.527167, and minimum is --4.753338 which has produced high degree of standard deviation to 1 (1.001268). There exist negative skewness (-0.051602) which represents an asymmetric tail which exceeds towards negative. The returns on the portfolio of the daily closing index of CSI300 are more or less normally distributed. The stock returns exhibits non-normality. If the returns are normally distributed, then coefficients of skewness and excess kurtosis should be equal to zero. The skewness (-0.051602) and kurtosis (4.746702) indicates that there exist normality in the daily closing return series of CSI300.

Volatility Clustering

Volatility clustering implies a strong auto correlation in squared returns. The easy method of estimating volatility clustering is to calculate the first-order autocorrelation in squared returns. In order to test the joint hypothesis that all the serial correlations of the returns for lags 1 through k are simultaneously equal to zero, the researcher uses the Ljung Box Pierce (Q statistic) developed by Ljung and Box, which is defined as

$$Q = n\,(n + 2) \sum r^2 k \;\; / \, (n\text{-}k)$$

Where n= sample size and k= lag length (Ljung and Box, 1978). In an application, if the computed Q exceeds the critical Q value from the Chi square table at the chosen level of significance, the researcher can reject the null hypothesis that all rk are zero. Autocorrelation in the raw return series and its square is indicative of volatility clustering. These features suggest in making use of GARCH model for this kind of data set.

Table 2 & 3 (Appendix) exhibits the auto correlation for residuals of the daily closing returns for the BRIC countries stock market index. Table 4 & 5 (Appendix) exhibits the autocorrelation test squared Residuals of daily closing returns for the BRIC countries stock market index. Using Ljung-Box (L-B) Q-statistics, the researcher detects autocorrelation and its associated probability values. If the probability value is greater than 0.05, we accept the null hypothesis (it suggests absence of autocorrelation). In a situation where probability value is less than 0.05, we reject the null hypothesis (it suggests presence of autocorrelation).

We computed Q-statistics up to 20 lags for both raw returns and their square to test for GARCH effect for all the daily closing returns for index of BRIC countries

Brazil (IBOVESPA): The Ljung Box Pierce (Q statistic) upto 20 lags for raw returns is28.984, p value is 0.088, Auto correlation (AC) is 0.029 and Partial Auto Correlation (PAC) is 0.27. The TheLjung Box Pierce (Q statistic) up to 20 lags for squared return is 37.042, p value is 0.012, Auto correlations (AC) is 0.023 and Partial Auto correlation (PAC) is 0.024. The probability value is greater than 0.05, thus it suggests absence of autocorrelation. All the lags are statistically significant, and the squares of the lag values are larger, suggesting that GARCH (1,1) type modeling is more appropriate (Nelson, 1991).

Russia (RTSI): The Ljung Box Pierce (Q statistic) up to 20 lags for raw returns is59.484, Auto correlation (AC) is 0.005 and Partial Auto Correlation (PAC) is 0.002. The TheLjung Box Pierce (Q statistic) up to 20 lags for squared return is 8.6084, p value is 0.987, Autocorrelation

(AC) returns is 0.004 and partial auto correlation (PAC) is 0.004. The probability value is greater than 0.05, thus it suggests absence of autocorrelation All the lags are statistically significant, and the squares of the lag values are larger, suggesting that GARCH (1,1) type modeling is more appropriate (Nelson, 1991).

India (S&P NIFTY): The Ljung Box Pierce (Q statistic) up to 20 lags for raw returns is55.154, Auto correlation (AC) is 0.032 and Partial Auto Correlation (PAC) is 0.028. The TheLjung Box Pierce (Q statistic) upto 20 lags for squared return is14.528, p value is0.803, Autocorrelation (AC) returns is 0.002, partial auto correlation (PAC) is 0.003. The probability value is greater than 0.05, thus it suggests absence of autocorrelation All the lags are statistically significant, and the squares of the lag values are larger, suggesting that GARCH (1,1) type modeling is more appropriate (Nelson, 1991).

China (CSI300): The Ljung Box Pierce (Q statistic) upto 20 lags for raw returns is43.518, p-value is 0.002, Auto correlation (AC) is 0.007 and Partial Auto Correlation (PAC) is 0.007. The TheLjung Box Pierce (Q statistic) up to 20 lags for squared return is 15.365, p value is 0.755, Autocorrelation (AC) returns is0.008, partial auto correlation (PAC) is 0.006. The probability value is greater than 0.05, thus it suggests absence of autocorrelation All the lags are statistically significant, and the squares of the lag values are larger, suggesting that GARCH (1,1) type modeling is more appropriate (Nelson, 1991).

HETEROSCEDASTICITY TEST

Table 6 (Appendix) exhibits the ARCH -LM for lag 10 for IBOVESPA, RTSI, CSI300, and S&P NIFTY indicates the presence of conditional heteroscedasticity for ARCH (1). Consequently, we estimated model for GARCH (1, 1) for the daily closing returns of BRIC countries stock market index. With wider tail distribution, the GARCH model is reasonable for explaining the data. (Ghulam Ali, 2013).

In case of Brazil **(IBOVESPA)**, results of the heteroskedasticity test for lag 10 reveals that F statistics is 2.705922 and its probability level as 0.0026. For Russia **(RTSI)**, F statistics is 0.568053 and its probability level as 0.8412. For **(S&P NIFTY)**, India, the F statistics is 0.836247 and its probability level is 0.5935. In case of **China (CSI300)**, F statistics is 0.314247, and its probability level is 0.9778. Thus all the indices of the BRIC countries reveal conditional heteroskedascity.

GARCH Model Fitting

The Ljung-Box Q-statistics also corroborates absence of any autocorrelations in the standardized square residuals when GARCH (1, 1) model is used. Table 7 (Appendix) exhibits the GARCH (1,1) estimations for IBOVESPA, RTSI, S&P NIFTY, CSI300. The conditional variance equation is then presented in the following form.

For time series analysis, it is desirable to have stationary series. Stationarity of the series can be found by summation of $\alpha+\beta$ and the value of this summation should be less than unity. The stationarity condition ($\alpha + \beta < 1$) is satisfied here. A large value of GARCH lag coefficients β_1 indicates that shocks to conditional variance takes a long time to die out, so the volatility is 'persistent'. Low value of error coefficient α_1 suggests that large market surprises induce relatively small revisions in future volatility.

Brazil (IBOVESPA): α = 0.101305, which exhibits the impact of the good news, β is ARCH effect, β = 0.877747, which exhibits impact of the bad news. β is the GARCH effect. The conditional variance equation for Brazil (IBOVESPA) is presented in the following form.

$$h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i h_{t-i}$$

$$h_t = 0.085427 + \sum_{i=1}^{q} 0.101305_i \pounds_{t-i}^2 + \sum_{i=1}^{p} 0.877747 h_{t-i}$$

(α+ β) = 0.101305+0.877747= 0.979052

= (α+ β) < 1

For time series analysis, it is desirable to have stationary series. Stationarity of the series can be found by summation of $\alpha+\beta$ and the value of this summation should be less than unity. The stationarity condition ($\alpha+\beta$ < 1) is satisfied here. Here the value of α is +0.101305 and the value of β is +0.877747. A big value of GARCH lag coefficients β (+0.877747) indicates that shocks to conditional variance takes a long time to die out, so the volatility is 'persistent'. Low value of error coefficient α (0.101305) suggests that large market surprises induce relatively small revisions in future volatility.

Here, $\alpha + \beta$ = 0.979052 which is close to unity and therefore it can be stated that a 'shock' at time t persists for many future periods. A soaring value of this kind implies a 'elongated memory' in the stock market. Any shock will lead to a everlasting change in all future values of ht; hence shocks to conditional variance are 'persistent.' Brazilian stock markets are volatile. The relatively small market capitalization and illiquidity of Brazilian equity markets may cause the price of securities of Brazilian issuers to fluctuate.

RUSSIA (RTSI): α = 0.007538, which exhibits the good news, α is ARCH effect, β = 0.861868, which exhibits impact of the bad news. β is the GARCH effect. The conditional variance equation for Russia (RTSI) is presented in the following form.

$$h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^{\ 2} + \sum_{i=1}^{p} \beta_i h_{t-i}$$

$$h_t = 0.092662 + \sum_{i=1}^{q} 0.128096 £_{t-i}^{\ 2} + \sum_{i=1}^{p} {}_i\, 0.861868 h_{t-i}$$

(α+ β) = 0.128096+0.861868=0.0.989964

= (α+ β) < 1

For time series analysis, it is desirable to have stationary series. Stationarity of the series can be found by summation of $\alpha+\beta$ and the value of this summation should be less than unity. The stationarity condition ($\alpha+\beta$ < 1) is satisfied here. Here the value of α is +0.128096 and the value of β is +0.861268. A big value of GARCH lag coefficients β (+0.861268) indicates that shocks to conditional variance takes a long time to die out, so the volatility is 'persistent'. Low value of error coefficient α (0.128096) suggests that large market surprises induce relatively small revisions in future volatility.

Here, $\alpha+\beta$ = 0.989964 which is close to unity and therefore it can be highlighted that a 'shock' at time t persists for many future periods. A soaring value of this kind implies a 'elongated memory' in the stock market. Any shock will lead to everlasting change in all future values of ht; hence shocks to conditional variance are 'persistent.' Russian stocks have become the most volatile since 2009. The shocking political circumstances are bumping up against the financial markets.

INDIA (S&P NIFTY): α = 0.110126, which exhibits the good news, α is GARCH effect, β = 0.876838 which exhibits the impact of the bad news, α is the GARCH effect. The conditional variance equation for India (S&P NIFTY) is presented in the following form.

$$h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^{\ 2} + \sum_{i=1}^{p} \beta_i h_{t-i}$$

$$h_t = 0.047085 + \sum_{i=1}^{q} 0.110126\ £_{t-i}^{\ 2} + \sum_{i=1}^{p} {}_i\, 0.876838 h_{t-i}$$

= (α+ β) = 0.110126+0.876838=0.986964

= (α+ β) < 1

For time series analysis, it is desirable to have stationary series. Stationarity of the series can be found by summation of $\alpha+\beta$ and the value of this summation should be less than unity. The stationarity condition ($\alpha+\beta$<1) is satisfied here. Here the value of α is +0.110126 and the value of β is +0.876838. A big value of GARCH lag coefficients β (+0.876838) indicates that shocks to conditional variance takes a long time to die out, so the volatility is 'persistent'. Low value of error coefficient α (0.110126) suggests that large market surprises induce relatively small revisions in future volatility.

Here, $\alpha+\beta$ = 0.986964 which is close to unity and therefore it can be proved that a 'shock' at time t persists for many future periods. A soaring value of this kind implies a 'elongated memory' in the stock market. Any shock will lead to a everlasting change in all future values of ht; hence shocks to conditional variance are 'persistent.'

CHINA (CSI300): α = 0.05902, which exhibits the good news, β is ARCH effect, β = 0.931367 which exhibits the impact of the bad news, β is the GARCH effect. The conditional variance equation for China (CSI300) is presented in the following form.

$$h_t = \sim_0 + \sum_{i=1}^{q} \sim_i \pounds_{t-i}{}^2 + \sum_{i=1}^{p} \; {}_i h_{t-i}$$

$$h_t = 0.02813 + \sum_{i=1}^{q} 0.05902 \; \pounds_{t-i}{}^2 + \sum_{i=1}^{p} 0.931367 h_{t-i}$$

= (α+ β) =0.05902+0.93136 = 0.990387

= (α+ β) < 1

For time series analysis, it is desirable to have stationary series. Stationarity of the series can be found by summation of $\alpha+\beta$ and the value of this summation should be less than unity. The stationarity condition ($\alpha+\beta$ < 1) is satisfied here. Here the value of α is +0.05902 and the value of β is +0.931367. A big value of GARCH lag coefficients β (+0.931367) indicates that shocks to conditional variance takes a long time to die out, so the volatility is 'persistent'. Low value of error coefficient α (0.05902) suggests that large market surprises induce relatively small revisions in future volatility. (Kaniel, R., Saar, G., and Titman, S. (2008).

Here, $\alpha+\beta$ = 0.990387which is close to unity and therefore it can be said that a 'shock' at time t persists for many future periods. A soaring value of this kind implies a 'elongated memory' in the stock market. Any shock will lead to a everlasting change in all future values of ht; hence shocks to conditional variance are 'persistent.'

Among all the BRIC countries ($\alpha+\beta$) is higher in China S&P CSI300 (0.990387) which highlights that Chinese stock markets are highly volatile followed by Russia RTSI (0.989964) and India S&P NIFTY (0.986964) and Brazil IBOVESPA (0.979052). China reflects high degree of volitity of series returns among the BRIC countries. This long-lasting volatility in the stock market has been disappointing issue for the retail investors to invest in equity markets and boosted the obsession towards bullion industry in china. Due to high volatility, new clients are afraid to burn their fingers and existing investors are uncomfortable in roiling their portfolio in china. This is consistent with the prior studies undertaken on individual investors in different countries. TabajaraPimenta Junior, Fabiano, et.al (2014) examines whether the capital market behavior of the BRIC's emerging countries in the 2008 international crisis had already been equivalent to that of industrialized countries (USA, Japan, United kingdom, Germany). The researchers apply three uni-variate econometric approaches for modeling the market volatilities (GARCH, EGARCH, TGARCH). Results reveal that there exists similar volatility, volatility asymmetry and delayed volatility reaction to market changes. The authors conclude that the BRIC's markets showed persistence to volatility shocks, less asymmetry and faster reactions of volatility to market changes.

Determination of Goodness of fit model

The Akaike info criterion (AIC), Schwarz criterion (SIC), Hannan-Quinn criterion (HQ), and Log likelihood are considered to determine the goodness of fit model as exhibited in Table 8 (appendix).

Brazil (IBOVESPA): AIC (3.994235), SIC (4.001205), HQ (3.996688) and log likelihood (-9217.69) which determines GARCH (1,1) estimations as the best fit model for volatility estimations.

Russia (RTSI): AIC (4.307076), SIC (4.314648), HQ (4.309754) and log likelihood (-9009.71) which determines GARCH (1,1) estimations as the best fit model for volatility estimations.

India (S&P NIFTY): AIC (3.550617), SIC (3.557539), HQ (3.553052) and log likelihood (-8260.84) which determines GARCH (1,1) estimations as the best fit model for volatility estimations.

China (CSI300): AIC (3.706397), SIC (3.716236), HQ (3.709932) and log likelihood (-5671.35) which determines GARCH (1,1) estimations as the best fit model for volatility estimations.

Stock Market Volatility forecasting Evaluation

There exists wide range of statistics to evaluate and compare forecast errors in the literature of volatility forecasting. The most popularly used measures in the literature include mean error (ME), root mean square error (RMSE), mean absolute percentage error (MAPE) and mean absolute error (MAE) and Theil Inequality Coefficient.

Table 9 (Appendix) exhibits the forecast evaluation test for GARCH (1,1) estimation for daily closing returns of the BRIC countries. In case of Brazil IBOVESPA exhibits RMSE (2.103984), MAE (1.466873), MAPE (118.3452), Theil Inequality co-efficient (0.953963), Bias proportion (0.000422), Variance proportion (0.981761), and covariance proportion (0.017817) which is unanimously favored.

For **Russia (RTSI)** exhibits RMSE (2.814817), MAE (1.784799), MAPE (126.7947), Theil Inequality co-efficient (0.945539),Bias proportion (0.000566), Variance proportion (0.910458) and covariance proportion (0.088976) which bring out the fact the forecast of GARCH (1,1) is highly desirable

For **India (S&P NIFTY)** the forecast evaluation measures RMSE (1.616662), MAE (1.410520), MAPE (122.4337), Theil Inequality co-efficient (0.929369), Bias proportion (0.000703), Variance proportion (0.907197), Co variance proportion (0.092100) which bring out the fact the forecast of GARCH (1,1) is predicts accuracy.

In case of **China (CSI300)**, RMSE (1.715445), MAE (1.208841), MAPE (101.0135), Theil Inequality co-efficient (0.996279), Bias proportion (0.000028), Variance proportion (0.994690) and covariance proportion (0.005281) which bring out the fact the forecast of GARCH (1,1) is highly desirable and favored.

CONCLUSION AND IMPLICATIONS

The present study brings out clearly that the financial market volatility has significantly increased. Higher volatility is both a gesture and a vehicle of uncertainty. The social cost associated with high volatility was serious during the period 1st April 1996 to 31st August 2014. Genuine investors lost optimism and deceased from the market. Volatility index was introduced by the Chicago Board of Options Exchange in 1993 called the VIX, which is acts the new barometer of investor fear. In broad-spectrum, VIX is often mentioned as the investor fear gauge, mainly because it measures perceived stock market volatility-both upside as well as downside volatility. Sarwar, G. (2012) When the VIX level is low, it implies that investors are hopeful and contented rather than timid in the market, which indicates that investors perceive no or low potential risk. (Siriopoulos, C., and Fassas, A. 2012). Even, Credit rating agencies act as driver of the stock market volitity. Any ratings news, if it provides new information, has a positive externality, since it reduces credit risk, and a negative externality, since it increases volatility risk. Credit rating agencies play an significant part in providing one source of information that aids accuracy and market capability, thereby plummeting the imbalance of information among the stock market investors. Engorgement of corporate scams and controversies has shocked investor's confidence in equities. The great fright arises in the investor's mind whether the rating agencies supports their interest by guiding them in the precise path. Investors have seen their life span savings washed out with unsupportive and erroneous assistance of CRAs. Credit agencies fuelled global financial crisis by performing the biased job in absurd manner. But have they been of value to investors?

REFERENCES

- Bollerslev, T. (1986) Generalized autoregre-ssive conditional heteroscedasticity, Journal of Econometrics, 31, 307-27.
- Brooks, C. (1998) Predicating stock index volitity: Can market volume help?, Journal of Forecasting, 17, 59-80
- Engle, R. F. (1982) Auto regressive conditional heteroscedasticity with estimates of the variance of United kingdom inflation, Econometrica, 50, 987-1007.
- Fair, R C and Shiller, RJ (1989). The Informational Content of Ex-ante Forecasts, Review of Economics and Statistics, 71(2), May, 325-332.
- Fair, R C and Shiller, RJ (1990).Comparing

Information in Forecasts from Econometric Models, American Economic Review, 80(3), 375-380.

- Fama, E. (1965). The Behavior of Stock-market Prices.Journal of Business, 38(1): 34-105.
- French, K. (1980). Stock Returns and the Weekend Effect. Journal of Financial Economics, 8: 55-69.
- Glosten, L ., Jaganathan R and Runkle, D. (1993) Relationship between the expected value and volatility of the nominal excess returns on Stocks", Journal of Finance, Vol. 48, pp.1779-802
- Hamilton, J. D. (1994) Time Series Analysis, Princeton, New Jersey
- JatinTrivedi and Ramona Birau (2013) Estimating Emerging stock market volatility using GARCH family models, Indian Journal of Applied Research, Vol 3, Issue 9, Sep 2013.
- Jun Y U (2002) Forecasting Volatility in the New Zealand stock market, Applied Financial Economics, 12, 193-202
- Kaniel, R., Saar, G., and Titman, S. (2008). Individual Investor Trading and Stock Returns.Journal of Finance, 63: 273-310.
- Pagan, A and Schwert, G W (1990). Alternative Models for Conditional Stock Volatilities, Journal of Econometrics, 45(1/2), 267-290
- Pandey, A. (2005). Volatility Models and Their Performance in Indian Capital Markets.Vikalpa, 30(2): 27-46.
- Poon, S.H., and Granger, C. (2003). Forecasting Financial market Volatility: A Review. Journal of Economic Literature, 41(2): 478-539.
- RuchikaGahlot, Saroj Kumar Datta (2012) Impact of future trading on stock market: a study of BRIC Countries, Studies in Economics and Finance, Vol.29 Issue 2, pp.118-132
- Sarwar, G. (2012). Is VIX an Investor Fear gauge in BRIC equity markets? Journal of Multinational Financial Management, 22(3), 55-65.
- Siriopoulos, C., and Fassas, A. (2012). An Investor Sentiment Barometer: Greek Volatility Index (GRIV). Global Finance Journal, 23(2): 77-93.
- TabajaraPimenta Junior, FabianoGuasti Lima and Luzi Eduardo Gaio (2014). Volatility behavior of BRIC capital markets in the 2008 international financial crisis,african journal of business management, Vol.8(11), pp. 373-381, June 2014

Appendix

Table 1

Descriptive Statistics for BRIC countries

Descriptive Statistics	Brazil IBOVESPA	Russia RTSI	India S&P NIFTY	China CSI300
Mean	0.030642	0.030250	0.032168	0.001631
Median	0.004507	0.011318	0.001957	0.032884
Maximum	5.471292	4.961839	7.690612	5.527167
Minimum	5.476607	9.506609	6.670432	4.753338
St. Deviation	0.999198	0.999941	0.999615	1.001268
Skewness	0.278726	0.438555	0.250807	0.051602
Kurtosis	4.261334	6.825759	5.709933	4.746702
JarqueBera	365.9218	2687.020	1473.498	390.7390
Probability	0.000000	0.000000	0.000000	0.000000

Source: Computed Data

Table 2
Auto Correlation Test For Residuals

	Brazil (IBOVESPA)				Russia (RTSI)			
Lag	AC	PAC	Q-statistics	Prob	AC	PAC	Q-statistics	Prob
1	0.041	0.041	7.8847	0.005	0.103	0.103	44.524	0
2	0.002	0	7.9029	0.019	0.005	-0.006	44.618	0
3	0.01	0.01	8.3817	0.039	0.014	0.015	45.495	0
4	0.01	0.009	8.8041	0.066	0.009	0.006	45.844	0
5	0.005	0.004	8.8981	0.113	0.001	-0.001	45.847	0
6	0.005	0.005	9.0182	0.173	0.013	0.013	46.61	0
7	0.005	0.005	9.1337	0.243	0.023	0.02	48.858	0
8	0.012	0.011	9.7777	0.281	0.026	0.022	51.781	0
9	0.011	0.01	10.373	0.321	0.024	0.019	54.247	0
10	0.046	0.045	19.958	0.03	0.008	0.003	54.516	0
11	0.008	0.005	20.284	0.042	-0.003	-0.005	54.543	0
12	0.007	0.007	20.513	0.058	0.009	0.008	54.848	0
13	0.002	0.003	20.53	0.083	0.02	0.018	56.581	0
14	0.015	0.016	21.559	0.088	-0.01	-0.015	57.028	0
15	0.019	0.018	23.155	0.081	-0.001	0.001	57.029	0
16	0.013	0.012	23.982	0.09	-0.017	-0.019	58.217	0
17	0.003	0.002	24.023	0.119	-0.004	-0.001	58.281	0
18	-0.009	-0.01	24.389	0.143	-0.012	-0.012	58.843	0
19	0.011	0.011	24.949	0.162	0.011	0.014	59.397	0
20	0.029	0.027	28.984	0.088	0.005	0.002	59.484	0

Source: Computed Data

Table 3
Auto Correlation Test For Residuals

	India (S&P NIFTY)				China (CSI300)			
Lag	AC	PAC	Q-statistics	Prob	AC	PAC	Q-statistics	Prob
1	0.052	0.052	12.417	0	0.028	0.028	2.4078	0.121
2	-0.01	-0.012	12.854	0.002	-0.002	-0.003	2.4168	0.299
3	0.025	0.027	15.835	0.001	0.046	0.046	8.9628	0.03

4	0.031	0.028	20.357	0	0.022	0.019	10.395	0.034
5	0.008	0.005	20.652	0.001	0.013	0.012	10.898	0.053
6	-0.038	-0.039	27.458	0	-0.041	-0.044	16.136	0.013
7	0.01	0.013	27.914	0	0.04	0.04	20.973	0.004
8	-0.004	-0.007	27.975	0	-0.002	-0.006	20.982	0.007
9	0.031	0.034	32.482	0	0.008	0.012	21.177	0.012
10	0.027	0.026	35.938	0	0.055	0.052	30.427	0.001
11	-0.02	-0.022	37.771	0	0.035	0.032	34.169	0
12	-0.002	-0.002	37.786	0	0.019	0.014	35.259	0
13	0.005	0.002	37.892	0	0.007	0.005	35.411	0.001
14	0.033	0.031	42.914	0	0.023	0.015	37.005	0.001
15	-0.01	-0.009	43.358	0	0.03	0.026	39.804	0
16	-0.012	-0.009	44.067	0	-0.006	-0.005	39.912	0.001
17	0.028	0.025	47.7	0	-0.014	-0.017	40.485	0.001
18	-0.012	-0.017	48.369	0	0.027	0.024	42.778	0.001
19	-0.021	-0.02	50.407	0	-0.014	-0.018	43.369	0.001
20	-0.032	-0.028	55.154	0	-0.007	-0.007	43.518	0.002

Source: Computed Data

Table 4
Auto Correlation Test For squared Residuals

	Brazil (IBOVESPA)				Russia (RTSI)			
Lag	**AC**	**PAC**	**Q-statistics**	**Prob**	**AC**	**PAC**	**Q-statistics**	**Prob**
1	-0.011	-0.011	0.5155	0.473	0.01	0.01	0.4129	0.52
2	0.068	0.068	21.766	0	0.021	0.021	2.2403	0.326
3	0.017	0.018	23.087	0	0.007	0.006	2.4296	0.488
4	0.005	0.001	23.196	0	-0.015	-0.015	3.3291	0.504
5	0.002	0	23.212	0	-0.01	-0.01	3.7355	0.588
6	-0.007	-0.008	23.463	0.001	-0.014	-0.013	4.5269	0.606
7	-0.006	-0.007	23.651	0.001	-0.006	-0.005	4.6685	0.7
8	-0.023	-0.022	26.126	0.001	-0.005	-0.004	4.77	0.782
9	0.001	0.002	26.135	0.002	-0.01	-0.01	5.2055	0.816
10	0.011	0.015	26.715	0.003	-0.012	-0.012	5.8461	0.828

11	-0.022	-0.021	28.991	0.002	-0.011	-0.01	6.3208	0.851
12	0.004	0.001	29.048	0.004	-0.005	-0.005	6.4228	0.893
13	-0.019	-0.017	30.794	0.004	0.008	0.008	6.7041	0.917
14	0.006	0.005	30.948	0.006	-0.014	-0.014	7.4869	0.914
15	-0.005	-0.002	31.05	0.009	-0.007	-0.008	7.7229	0.934
16	-0.014	-0.015	31.958	0.01	-0.002	-0.002	7.7365	0.956
17	-0.017	-0.017	33.274	0.01	-0.011	-0.01	8.2001	0.962
18	0	0.002	33.274	0.015	-0.009	-0.009	8.5339	0.97
19	-0.016	-0.015	34.499	0.016	0	0	8.534	0.98
20	0.023	0.024	37.042	0.012	0.004	0.004	8.6084	0.987

Source: Computed Data

Table 5

Auto Correlation Test For squared Residuals (GARCH (1,1))

	India (S&P NIFTY)				China (CSI300)			
Lag	**AC**	**PAC**	**Q-statistics**	**Prob**	**AC**	**PAC**	**Q-statistics**	**Prob**
1	0.021	0.021	1.9595	0.162	-0.013	-0.013	0.5038	0.478
2	0.006	0.005	2.1117	0.348	0.01	0.01	0.7938	0.672
3	0.006	0.006	2.2947	0.514	-0.011	-0.011	1.1757	0.759
4	0	0	2.2953	0.682	0.008	0.007	1.3592	0.851
5	0	0	2.2953	0.807	-0.012	-0.011	1.7858	0.878
6	-0.004	-0.004	2.3578	0.884	-0.005	-0.006	1.8786	0.931
7	0	0	2.358	0.937	0.006	0.007	2.0075	0.959
8	-0.016	-0.016	3.5203	0.898	0.004	0.004	2.0546	0.979
9	-0.032	-0.031	8.2135	0.513	-0.007	-0.007	2.1948	0.988
10	0.008	0.009	8.484	0.582	0.02	0.02	3.392	0.971
11	-0.013	-0.013	9.2434	0.599	-0.02	-0.02	4.684	0.945
12	-0.012	-0.011	9.8791	0.627	0.042	0.041	10.015	0.615
13	0.012	0.012	10.52	0.651	0.01	0.012	10.32	0.668
14	0.001	0.001	10.528	0.723	-0.007	-0.009	10.476	0.727
15	-0.012	-0.013	11.227	0.736	-0.029	-0.028	13.024	0.6
16	-0.016	-0.016	12.391	0.717	-0.023	-0.024	14.602	0.554

17	-0.014	-0.014	13.307	0.715	-0.005	-0.005	14.682	0.618
18	-0.008	-0.008	13.636	0.752	-0.01	-0.01	15.005	0.662
19	0.014	0.015	14.51	0.753	-0.007	-0.008	15.174	0.711
20	-0.002	-0.003	14.528	0.803	0.008	0.006	15.365	0.755

Source: Computed Data

Table 6
Heterokodascity Test (ARCH -LM for lag 10)

Heterokodasicity	Brazil IBOVESPA	Russia RTSI	India S&P NIFTY	China CSI300
F Statistics	2.705922	0.568053	0.836247	0.314247
Prob F	0.0026	0.8412	0.5935	0.9778
ProbChisquare	0.0026	0.8408	0.5932	0.9777

Source: Computed Data

Table 7
GARCH ESTIMATIONS (1,1)

Variable		Coeffient	Std error	Z statistics	p-value
Brazil IBOVESPA	Constant	0.100428	0.023922	4.198135	0
	R(1)	0.00877	0.010044	-0.873004	0
	Variance Constant	0.085427	0.012349	6.917469	0
	ARCH effect	0.101305	0.005949	17.02826	0
	GARCH effect	0.877747	0.007633	114.988	0
Russia RTSI	Constant	0.132693	0.02528	5.249026	0
	R(1)	-0.04142	0.007162	-5.78417	0
	Variance Constant	0.092662	0.006746	13.73638	0
	ARCH effect	0.128096	0.007538	16.99365	0
	GARCH effect	0.861868	0.006403	134.5972	0
India S&P NIFTY	Constant	0.087127	0.018072	4.821198	0
	R(1)	0.049056	0.008587	5.712487	0
	Variance Constant	0.047085	0.004954	9.505103	0
	ARCH effect	0.110126	0.005824	18.90763	0
	GARCH effect	0.876838	0.005368	163.3331	0
China CSI300	Constant	0.009174	0.024371	0.376419	0.7066
	R(1)	0.002689	0.015771	0.17048	0.8646
	Variance Constant	0.02813	0.006196	4.53986	0
	ARCH effect	0.05902	0.005707	10.34158	0
	GARCH effect	0.931367	0.006491	143.4904	0

Source: Computed Data

Table 8
GARCH ESTIMATIONS (1,1)

Stock Index	Akaike info criterion	Schwarz criterion	Hannan-Quinn criter.	Log likelihood
Brazil IBOVESPA	3.994235	4.001205	3.996688	-9217.69
Russia RTSI	4.307076	4.314648	4.309754	-9009.71
India S&P NIFTY	3.550617	3.557539	3.553052	-8260.84
China CSI300	3.706397	3.716236	3.709932	-5671.35

Source: Computed Data

Table 9
Forecast Evaluation Test for BRIC countries

Test Names	Brazil IBOVESPA	Russia RTSI	India S&P NIFTY	China CSI300
Root Mean Squared Error (RMSE)	2.103984	2.814817	1.616662	1.715325
Mean Absolute Error (MAE)	1.466876	1.784799	1.410520	1.208323
Mean Absolute Percent Error (MAPE)	118.3452	126.7947	122.4337	113.1077
Theil Inequality Co-efficient	0.953963	0.945539	0.929369	0.993937
Bias Proportion	0.000422	0.000566	0.000703	0.000028
Variance Proportion	0.981761	0.910458	0.907197	0.994690
Covariance Proportion	0.017817	0.088976	0.092100	0.005281

Source: Computed Data

Corrigendum : The paper Investors' Psychology : An empirical analysis published in *Management Insight* (Vol 10, No. 2) December 2014 stands withdrawn from the journal as it was printed inadvertently. The same is regretted.