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AN ANALYSIS OF STOCK MARKET VOLATILITY OF BRICS COUNTRIES

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ABSTRACT

Forecasting is an important area of research in financial markets and immense effort has been expended in improving the accuracy of forecasting models. Fund managers and investors in the stock market often attempt to forecast the stock price and volatility. Accuracy in forecasting the volatility with minimum error facilitates to anticipate the risk and return of portfolio. In this direction, the present paper attempts at modelling and forecasting the stock market volatility of the BRICS Nations. The primary objective is to fit the EGARCH model to estimate the market volatility based of the stock market indices of BRICS such as BM&FBOVESPA (Brazil), MICEX-RTS Group (Russia), National Stock Exchange (India), Shanghai Stock-Exchange (China) and Johannesburg Stock Exchange (South Africa). Based on forecasts and application of evaluation measures, the result shows that the return of China and South Africa fluctuates more than other countries.

Keywords: Volatility, ARCH, EGARCH, Volatility forecasts

1. INTRODUCTION

Volatility forecasting plays a very major role in the pricing of securities. With the rapid change in the financial market it is frequently heard from the traders about the fluctuation in the market due to different macroeconomics and other factors. Forecasting volatility accurately has become common topic of discussion for researcher, institution, professional, etc. It helps in the pricing of derivatives securities such as stock options and index options. Moreover, it gives idea to the investors regarding the movement of the market which helps them in the investment decision. Some researchers prefer Realised volatility or Historical Value over Implied Volatility.

Realised Volatility is calculated based on the past price movement of the securities. It is typically calculated as the standard deviation of the security's daily return over some past period. Corresponding to Realised Volatility, Implied Volatility is the by-product of an option pricing model. It is expression of the market's expectation of the future volatility between now and the option's expiration.

This study focuses on forecasting volatility of BRICS. The acronym BRICS stands for Brazil, Russia, India, China and South Africa. The term was coined by the Chief Economist of Goldman Sachs, in 2001, in a paper titled 'Building Better Global Economic BRICs' which looked at the growth of the four largest emerging economies later South Africa was added. Together the BRICS accounts for more than 40 percent of the global population and 30 percent in the world GDP (in PPP terms). The BRICS nations are all in developing or newly industrialized countries and they are distinguished by their large economies. The major stock market indices of BRICS have been taken as proxy to measure the market volatility. The indices considered for the study are listed below.

BM&FBOVESPA, Brazil was created in 2008 with the integration of the Brazilian Mercantile & Future Exchange (BM&F) and the Sao Paulo Stock Exchange. Together, the companies have formed the third largest exchange in the world in terms of market value.

MICEX-RTS Group, is the Russian stock and derivatives exchange. It came into existence in December 2011 after the merger of two main Russian exchanges, MICEX and RTS. The new exchange strives to achieve the status of an internationally competitive market through improved market infrastructure efficiency, product diversity and liquidity

NATIONAL STOCK EXCHANGE (NSE), India: is India's leading stock exchange covering various cities and towns across the countries. It was incorporated in November 1992.

Shanghai Stock-Exchange (SSE), China: It is based in the city of Shanghai China was established on December 19, 1990. SSE is the world's fifth largest stock market.

Johannesburg Stock Exchange, South Africa is the only stock exchange in South Africa that connects buyers and seller. The Johannesburg Stock Exchange offers the investor a first world trading environment, with world class technology and surveillance and settlement of securities in an emerging market context.

2. LITERATURE REVIEW

Considering the time-varying behaviour of volatility, ARCH model was developed by Engle (1982), which was further developed into GARCH model by Bollerslev (1986). Since then, a number of extensions of the basic GARCH model that are especially suited for estimating the conditional volatility of financial time series have been developed.

Ming Jing Yang (2012) studied The Forecasting Power of the Volatility Index in Emerging Markets: Evidence from the Taiwan Stock Market to explore the predictive power of the volatility index (VIX) in emerging markets from December 2006 to March 2010. The study show that the models including both the volatility indicator and the option market information have a stronger predictive power.

Tse Yiu Kuen; Tung, Siew Hoong (1992) studied Forecasting Volatility in the Singapore Stock Market, the Stock Exchange of Singapore (SES) are used to compare 3 methods of forecasting the volatility of derivative securities. The EWMA method is superior to the naive method and the GARCH model.

Timotheos Angelidis,Stavros Degiannakis (2005), analysed Forecasting one-day-ahead VaR and intra-day realized volatility in the Athens Stock Exchange Market. The aim is to evaluate the performance of symmetric and asymmetric ARCH models in forecasting both the one-day-ahead Value-at-Risk (VaR) and the realized intra-day volatility of two equity indices in the Athens Stock Exchange. Their result was that Under the VaR framework, the most appropriate method for the Bank index is the symmetric model with normally distributed innovations, while the asymmetric model with asymmetric conditional distribution applies for the General index.

Wei Liu, Bruce Morley (2009) studied the Volatility Forecasting in the Hang Seng Index using the GARCH Approach. The objective is to determine if forecasts from GARCH based models can outperform simple historical averaging models. The result shows that the GARCH models with non-Normal distributions show a robust volatility forecasting performance in comparison to the historical models.

Alex YiHou Huang (2011) studied Volatility forecasting in emerging markets with application of stochastic volatility model. This research examines the performance of five popular categories of volatility forecasting models on 31 emerging and developed stock indices with data series comprising recent 7 years. Their results shows that the equity markets of emerging markets are more volatile and difficult to model than those of developed countries.

Sasikanta Tripathy and Abdul Rahman (2013) compared between BSE and SSE Daily Stock Volatility and forecasted it using GARCH Model. To find out the stationarity of all the closing indices both for Sensex and SHCOMP, to know the return characteristics for both the stock exchanges through descriptive statistics, to measure the volatility for both the markets; To make a comparative study between BSE and SSE. Empirical results demonstrate that in both the stock markets, there are significant ARCH effects and it is appropriate to use the GARCH model to estimate the process.

3. OBJECTIVES

The primary objective is to estimate the stock market volatility of BRICS nations. The major indices of the respective countries have been considered to examine volatility. The indices considered for the study are BM&FBOVESPA, MICEX-RTS Group, National Stock Exchange, Shanghai Stock-Exchange, and Johannesburg Stock Exchange. The other objectives of the study are listed below

1. To examine whether the stock market returns of BRICS nations are

Stationary.

2. To analyse and compare the historical returns and volatility of BRICS nations.

3. To forecast the stock market volatility of BRICS nations

4. RESEARCH METHODOLOGY

4.1 Data Collection methods & Sources

The study is based on secondary data and it covers the period between 2011 and 2014. The daily closing price of BM&FBOVESPA, MICEX-RTS Group, National Stock Exchange, Shanghai Stock-Exchange, and Johannesburg Stock Exchange were taken as input for estimating volatility.

4.2 Tools applied for the study

The Exponential Generalized Autoregressive Conditional Heteroskedasticity (EGARCH) is applied in this study to forecast volatility. Descriptive statistics provides simple summaries about the sample and the observations that have been made. Residual diagnosis provides the correlation and normal distribution among the data. Correlogram analysis is used to check the randomness of the data. The goodness of fit of a statistical model describes how well it fits a set of observations. Measures of goodness of fit typically summarize the discrepancy between observed values and the values expected under the mode. These tests are done with the help of statistical software like MS Excel 2010 and NumXL.

4.3 Measurement of Volatility

Volatility, as described, refers to the fluctuation in the monthly closing values of BM&FBOVESPA, MICEX-RTS Group, NSE, SSE and JSE indices over 4 years. Here volatility has been measured as the standard deviation of the rates of return. The rates of returns have been computed by taking a logarithmic difference of prices of two successive periods. Symbolically, it may be stated as follows:

$$R_t = log_e(p_t/p_{t-1}) = log_e\,(p_t) - log_e\,(p_t)$$

where log_e is the natural logarithm, p_t and p_(t-1) are the closing prices for the two consecutive periods. The logarithmic difference is symmetric between up and down movements and is expressed in percentage terms. Further, as discussed in the previous research works of Liu and Hung (2010) that the volatility of returns is categorized by a number of facts such as volatility clusters, time-varying volatility, and leptokurtic behavior, introduction of GARCH model of Bollerslev (1986) and Engle (1982) has become an approved tool for modelling volatility and forecasting.

4.4 ARCH and EGARCH

Autoregressive conditional heteroskedasticity (ARCH) models are used to characterize and model observed time series. This model is used whenever there is reason to believe that, at any point in a series, the terms will have a characteristic size or variance. In particular, ARCH models assume the variance of the current error term or innovation to be a function of the actual sizes of the previous time periods' error terms: often the variance is related to the squares of the earlier innovations.

Exponential Generalized Autoregressive Conditional Heteroskedastic (EGARCH) model by Nelson (1991) is another form of the GARCH model. Formally, an EGARCH (p, q):

$$log\sigma^2{}_t = \omega + \sum_{k=1}^{q} \beta_k \, g(Z_{t-k}) + \sum_{k=1}^{p} \propto_k \, log\sigma^2{}_{t-k}$$

where,

g $(Z_t) = \theta(Z_t) + \lambda(|Z_t| - E(|Z_t|))$

$\sigma^2{}_t$ = conditional variance

$\omega, \beta, \alpha, \theta \; and \; \lambda$ = coefficients

Z_t = standard normal variable or generalized error distribution

The formulation for g (Z_t) allows the sign and the magnitude of Z_t to have separate effects on the volatility. This is particularly useful in an asset pricing context. Since log $log\sigma^2{}_t$ may be negative there are no (fewer) restrictions on the parameters.

5. EMPIRICAL RESULTS

5.1 Descriptive Statistics

Table 5.1 Descriptive Statistics of Monthly Returns for the period between Jan 2011 and December 2014

Basis	**Brazil**	**Russia**	**India**	**China**	**South Africa**
Mean	-0.61%	-0.01%	0.04%	0.29%	0.88%
Median	-0.00754	0.000335	0.000254	0.000519	0.014171
Maximum	-0.10879	0.004606	0.005327	0.187058	0.126943
Minimum	-0.12621	-0.00561	-0.00487	-0.15047	-0.14465

SD	5.45%	0.24%	0.23%	5.89%	6.40%
Skewness	-0.17	-0.24	0.02	0.49	-0.33
Kurtosis	0.18	-0.63	-0.35	1.60	-0.14

The table 5.1 shows the descriptive statistics of monthly returns of BRICS'stock indices. For BM&FBOVESPA, MICEX-RTS Group, National Stock Exchange, Shanghai Stock-Exchange, and Johannesburg Stock Exchange, the skewness statistics for monthly return is found to be different from zero, indicating that the return distribution is not symmetric. Brazil Russia and South Africa indices are left skewed distribution which means most values are concentrated on the right of the mean, with extreme values to the left whereas India and China shows right skewed distribution. Furthermore, the relatively large excess kurtosis suggests that the underlying data are Platykurtic distribution flatter than a normal distribution with a wider peak, which is more in the case of SSE, China compared with other countries. The results authenticate the well-known fact that monthly stock returns are not normally distributed but are Platykurtic and skewed, which depicts the volatility nature of stock markets.

5.2 Correlogram Analysis

The Correlogram is a commonly used tool for checking randomness in a data set. This randomness is ascertained by computing autocorrelations for data values at varying time lags. Correlation of a time series with its own past and future values- is called Autocorrelation. It is also referred as “lagged or series correlation”. Positive autocorrelation is an indication of a specific form of “persistence”, the tendency of a system to remain in the same state from one observation to the next. If a time series exhibits correlation, the future values of the samples probabilistically depend on the current & past samples. Thus the existence of autocorrelation can be exploited in prediction as well as modelling time series.

In order to find a proper model for the data collected and the forecasting of its volatility Auto correlation (ACF) and partial auto correlation (PACF) tests were done. The ACF and PACF plot does not indicate persistence across all the lags. Therefore the use of E-GARCH from the GARCH family found to be ideal is applied in forecasting volatility.

5.3 E GARCH modelling of volatility

The common phenomenon in time series data of financial, stock and commodities is the volatility reacts differently to negative returns than to positive ones. Therefore, the exponential GARCH (EGARCH) model that captures this phenomenon is used to model volatility. E- GARCH volatility modelling is done by using NumXL software

The output of EGARCH model is tabulated below

Table 5.2 EGARCH (1,1)

Parameters	Symbol	Brazil	Russia	India	China	South Africa
Long run mean	μ	-0.01	0.00	0.00	0.02	0.01
Constant in the conditional volatility equation	α0	-12.54	-9.86	-3.13	-3.90	-5.10
1st Coefficient of the ARCH component	α1	0.72	0.14	0.00	-0.57	-0.89
1st leverage coefficient	γ1	0.40	-1.64	-614.13	0.15	-0.44
1st coefficient of the GARCH component	β1	-0.87	0.19	0.75	0.27	0.13
Long run monthly volatility	VL	0.04113	0.00235	-0.00214	0.05108	0.03544

The table 5.2 shows the EGARCH (1, 1) model specific parameters of long run mean variance, ARCH and GARCH coefficients. Since the time series data of closing price of BRICS in non-stationary, the logarithmic monthly return of close price is considered as input to EGARCH model. The parameter values were optimised through calibration of E-GARCH model by using "NumXL" software. These parameters are substituted in the equation to calculate volatility of the monthly returns of close price of BRICS's from 2011 to 2014.

5.4 Residual Diagnosis

Table 5.3 Residuals (standardized) Analysis					
	Brazil	**Russia**	**India**	**China**	**South Africa**
Average	0.13	0.03	-0.01	-0.27	-
Long run monthly volatility	4.11%	0.235%	-0.214%	5.108%	3.544%
SD	1.11	1.01	1.01	1.21	-
Noise	TRUE	TRUE	TRUE	TRUE	TRUE
Skewness	Left skewed	Left skewed	Left skewed	Left skewed	Left skewed
Kurtosis	Platykurtic	Platykurtic	Platykurtic	Platykurtic	Platykurtic
Normal distribution?	TRUE	TRUE	TRUE	TRUE	TRUE
ARCH Effect?	FALSE	FALSE	FALSE	FALSE	FALSE
Goodness of fit					
Log likelihood function	76.08	217.92	221.56	62.36	-
Akaike Information Criterion	-141.15	-424.83	-432.12	-113.72	-
Stability check of model (Stationarity and positive variance)	1	1	1	1	1

The long run conditional mean for China is the highest followed by Brazil and South Africa. Fitness of Good shows that the data is fit for all the volatility forecast. The kurtosis again is Platykurtic which means most values are concentrated on the right of the mean, with extreme values to the left. Hence the residual diagnosis indicates best fit of the model

5.5 Volatility Forecast

EGARCH (1,1) model is simulated to forecast volatility for the next 24 months starting from Jan 2015 to Dec 2016. The monthly returns are taken as model input to predict future volatility. The model describes the variation of one step (local) volatility over time and volatility values that span over the next 24 months. The model output is tabulated below:

Table 5.4 Forecasted volatility of BM&FBOVESPA (Brazil) for the period between Jan 2015 to Dec 2016

Step	Mean	STD	TS	UL	LL
1	-1.46%	3.26%	3.26%	4.93%	-7.85%
2	-1.46%	5.04%	4.24%	8.42%	-11.34%
3	-1.46%	3.44%	4.00%	5.29%	-8.21%
4	-1.46%	4.80%	4.21%	7.95%	-10.88%
5	-1.46%	3.59%	4.10%	5.58%	-8.50%
6	-1.46%	4.63%	4.19%	7.62%	-10.54%
7	-1.46%	3.71%	4.12%	5.80%	-8.73%
8	-1.46%	4.50%	4.17%	7.37%	-10.29%
9	-1.46%	3.80%	4.13%	5.98%	-8.91%
10	-1.46%	4.41%	4.16%	7.18%	-10.10%
11	-1.46%	3.87%	4.14%	6.12%	-9.05%
12	-1.46%	4.34%	4.15%	7.04%	-9.96%
13	-1.46%	3.93%	4.14%	6.23%	-9.16%
14	-1.46%	4.28%	4.15%	6.93%	-9.86%
15	-1.46%	3.97%	4.14%	6.32%	-9.24%
16	-1.46%	4.24%	4.14%	6.85%	-9.78%
17	-1.46%	4.00%	4.13%	6.38%	-9.31%
18	-1.46%	4.21%	4.14%	6.79%	-9.72%
19	-1.46%	4.03%	4.13%	6.43%	-9.36%
20	-1.46%	4.19%	4.14%	6.75%	-9.67%
21	-1.46%	4.05%	4.13%	6.47%	-9.40%
22	-1.46%	4.17%	4.13%	6.71%	-9.64%
23	-1.46%	4.06%	4.13%	6.50%	-9.43%
24	-1.46%	4.16%	4.13%	6.69%	-9.61%

Table 5.5 Forecasted volatility of MICEX-RTS (Russia) for the period between Jan 2015 to Dec 2016

Step	Mean	STD	TS	UL	LL
1	0.0240%	0.3060%	0.3060%	0.5757%	-0.6237%
2	0.0240%	0.2481%	0.2785%	0.4622%	-0.5102%
3	0.0240%	0.2382%	0.2658%	0.4428%	-0.4908%
4	0.0240%	0.2363%	0.2587%	0.4391%	-0.4871%
5	0.0240%	0.2359%	0.2543%	0.4384%	-0.4864%
6	0.0240%	0.2358%	0.2513%	0.4382%	-0.4863%
7	0.0240%	0.2358%	0.2492%	0.4382%	-0.4862%
8	0.0240%	0.2358%	0.2475%	0.4382%	-0.4862%
9	0.0240%	0.2358%	0.2463%	0.4382%	-0.4862%
10	0.0240%	0.2358%	0.2452%	0.4382%	-0.4862%
11	0.0240%	0.2358%	0.2444%	0.4382%	-0.4862%
12	0.0240%	0.2358%	0.2437%	0.4382%	-0.4862%
13	0.0240%	0.2358%	0.2431%	0.4382%	-0.4862%
14	0.0240%	0.2358%	0.2426%	0.4382%	-0.4862%
15	0.0240%	0.2358%	0.2421%	0.4382%	-0.4862%
16	0.0240%	0.2358%	0.2418%	0.4382%	-0.4862%
17	0.0240%	0.2358%	0.2414%	0.4382%	-0.4862%
18	0.0240%	0.2358%	0.2411%	0.4382%	-0.4862%
19	0.0240%	0.2358%	0.2408%	0.4382%	-0.4862%
20	0.0240%	0.2358%	0.2406%	0.4382%	-0.4862%
21	0.0240%	0.2358%	0.2404%	0.4382%	-0.4862%
22	0.0240%	0.2358%	0.2402%	0.4382%	-0.4862%
23	-0.0240%	0.2358%	0.2400%	0.4382%	-0.4862%
24	0.0240%	0.2358%	0.2398%	0.4382%	-0.4862%

Table 5.6 Forecasted volatility of NSE (India) for the period between Jan 2015 to Dec 2016

Step	Mean	STD	TS	UL	LL
1	0.04%	0.24%	0.24%	0.52%	-0.43%
2	0.04%	0.24%	0.24%	0.50%	-0.42%
3	0.04%	0.23%	0.24%	0.49%	-0.41%
4	0.04%	0.23%	0.23%	0.48%	-0.40%
5	0.04%	0.22%	0.23%	0.48%	-0.39%
6	0.04%	0.22%	0.23%	0.47%	-0.39%
7	0.04%	0.22%	0.23%	0.47%	-0.38%
8	0.04%	0.22%	0.23%	0.47%	-0.38%
9	0.04%	0.22%	0.23%	0.47%	-0.38%
10	0.04%	0.22%	0.22%	0.47%	-0.38%
11	0.04%	0.21%	0.22%	0.46%	-0.38%
12	0.04%	0.21%	0.22%	0.46%	-0.38%
13	0.04%	0.21%	0.22%	0.46%	-0.38%
14	0.04%	0.21%	0.22%	0.46%	-0.38%
15	0.04%	0.21%	0.22%	0.46%	-0.38%
16	0.04%	0.21%	0.22%	0.46%	-0.38%
17	0.04%	0.21%	0.22%	0.46%	-0.38%
18	0.04%	0.21%	0.22%	0.46%	-0.38%
19	0.04%	0.21%	0.22%	0.46%	-0.38%
20	0.04%	0.21%	0.22%	0.46%	-0.38%
21	0.04%	0.21%	0.22%	0.46%	-0.38%
22	0.04%	0.21%	0.22%	0.46%	-0.38%
23	0.04%	0.21%	0.22%	0.46%	-0.38%
24	0.04%	0.21%	0.22%	0.46%	-0.38%

Table 5.7 Forecasted volatility of MICEX-RTS (China) for the period between Jan 2015 to Dec 2016

Step	Mean	STD	TS	UL	LL
1	1.73%	2.18%	2.18%	6.00%	-2.53%
2	1.73%	4.07%	3.26%	9.70%	-6.24%
3	1.73%	4.81%	3.85%	11.15%	-7.69%
4	1.73%	5.03%	4.17%	11.58%	-8.12%
5	1.73%	5.09%	4.37%	11.70%	-8.24%
6	1.73%	5.10%	4.50%	11.73%	-8.27%
7	1.73%	5.11%	4.59%	11.74%	-8.28%
8	1.73%	5.11%	4.66%	11.74%	-8.28%
9	1.73%	5.11%	4.71%	11.74%	-8.28%
10	1.73%	5.11%	4.75%	11.74%	-8.28%
11	1.73%	5.11%	4.79%	11.74%	-8.28%
12	1.73%	5.11%	4.81%	11.74%	-8.28%
13	1.73%	5.11%	4.84%	11.74%	-8.28%
14	1.73%	5.11%	4.86%	11.74%	-8.28%
15	1.73%	5.11%	4.87%	11.74%	-8.28%
16	1.73%	5.11%	4.89%	11.74%	-8.28%
17	1.73%	5.11%	4.90%	11.74%	-8.28%
18	1.73%	5.11%	4.91%	11.74%	-8.28%
19	1.73%	5.11%	4.92%	11.74%	-8.28%
20	1.73%	5.11%	4.93%	11.74%	-8.28%
21	1.73%	5.11%	4.94%	11.74%	-8.28%
22	1.73%	5.11%	4.95%	11.74%	-8.28%
23	1.73%	5.11%	4.96%	11.74%	-8.28%
24	1.73%	5.11%	4.96%	11.74%	-8.28%

Table 5.8 Forecasted volatility of Johannesburg Stock Exchange (South Africa) for the period between Jan 2015 to Dec 2016

Step	Mean	STD	TS	UL	LL
1	0.04%	0.24%	0.24%	0.52%	-0.43%
2	0.04%	0.24%	0.24%	0.50%	-0.42%
3	0.04%	0.23%	0.24%	0.49%	-0.41%
4	0.04%	0.23%	0.23%	0.48%	-0.40%
5	0.04%	0.22%	0.23%	0.48%	-0.39%
6	0.04%	0.22%	0.23%	0.47%	-0.39%
7	0.04%	0.22%	0.23%	0.47%	-0.38%
8	0.04%	0.22%	0.23%	0.47%	-0.38%
9	0.04%	0.22%	0.23%	0.47%	-0.38%
10	0.04%	0.22%	0.22%	0.47%	-0.38%
11	0.04%	0.21%	0.22%	0.46%	-0.38%
12	0.04%	0.21%	0.22%	0.46%	-0.38%
13	0.04%	0.21%	0.22%	0.46%	-0.38%
14	0.04%	0.21%	0.22%	0.46%	-0.38%
15	0.04%	0.21%	0.22%	0.46%	-0.38%
16	0.04%	0.21%	0.22%	0.46%	-0.38%
17	0.04%	0.21%	0.22%	0.46%	-0.38%
18	0.04%	0.21%	0.22%	0.46%	-0.38%
19	0.04%	0.21%	0.22%	0.46%	-0.38%
20	0.04%	0.21%	0.22%	0.46%	-0.38%
21	0.04%	0.21%	0.22%	0.46%	-0.38%
22	0.04%	0.21%	0.22%	0.46%	-0.38%
23	0.04%	0.21%	0.22%	0.46%	-0.38%
24	0.04%	0.21%	0.22%	0.46%	-0.38%

5.6 Discussion

The analysis of stock market returns of BRICS nations shows significant fluctuations in the returns of China and South Africa. India and Russia has given stable return during the period of observation. The volatility forecasted by E-GARCH shows that South Africa has the highest volatility followed by Brazil, Russia, India and China. The term structure of volatility shows that Russia, India and China have persistent long term volatility (as per period of holding) whereas Brazil has least term structure volatility. The expected return is high from India and South Africa as compared to other BRICS nations

7. CONCLUSION

Stock market volatility has many implications for the real economy. Forecasting stock market is essential in finance areas such as option pricing, VaR applications and selection of a portfolio. Volatility forecasting is an important area of research in financial markets and this paper analyses the comparative relationship of BRICS's nation stock exchange using different statistical stools to forecast the volatility. Empirical results demonstrate that in both the stock markets, there are significant ARCH effects and it is appropriate to use the GARCH model to estimate the process.

References

1. Huang, Alex Y. (2011) Volatility forecasting in emerging markets with application of stochastic volatility model. Applied Financial Economics, 21(9), 665-681.
2. Sasikanta Tripathy and Abdul Rahman (2013). Forecasting Daily Stock Volatility Using GARCH Model: A Comparison Between BSE and SSE. The IUP Journal of Applied Finance.
3. Timotheos Angelidis,Stavros Degiannakis.(2005). Forecasting One-Day-Ahead VaR and Intra-Day Realized Volatility in the Athens Stock Exchange Market. Managerial Finance.34(7). Pp 489- 497
4. Tse Yiu Kuen, Tung Siew Hoong. (1992). Asia Pacific Journal of Management. Volume 9, Issue 1, pp 1-13
5. Wei Liu, Bruce Morley(2009). Volatility Forecasting in the Hang Seng Index using the GARCH Approach. Asia-Pacific Financial Markets. Volume 16, Issue 1, pp 51-63
6. Yang, M. J., & Liu, M. Y. (2012). The forecasting power of the volatility index in emerging markets: evidence from the Taiwan stock market. International Journal of Economics and Finance, 4(2), 217.