Volatility in BRIC Stock Markets

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Abstract

The study investigated the stock market volatility in the emerging stock markets of Brazil, Russia, India and China (BRIC) using daily closing price from January 1, 2009 to July 7, 2014. The results detect the presence of non-linearity through BDSL test while conditional Heteroscedasticity is identified through ARCH-LM test. The findings reveal that the GARCH (1,1) model successfully captures nonlinearity and volatility clustering. The analysis suggests that the persistence of volatility in Indian and Chinese stock markets is more than Brazil and Russia.

Key Words

Volatility clustering, nonlinearity, BDSL, GARCH

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I. Introduction

Volatility in equity market has become a matter of mutual concern in recent years for investors, regulators and brokers. Stock return volatility hinders economic performance through consumer spending[1]. Stock Return Volatility may also affect business investment spending[2]. Further the extreme volatility could disrupt the smooth functioning of the financial system and lead to structural or regulatory changes. Volatility of stock returns in the developed countries has been studied extensively. After the seminal work of Engle (1982) on Autoregressive Conditional Heteroscedasticity (ARCH) model on UK inflation data and its Generalized form GARCH(Generalized ARCH) by Bollerslev (1986), much of the empirical work used these models and their extensions (See French, Schwert and Stambaugh 1987, Akgiray 1989, Schwert, 1990, Chorhay and Tourani,1994, Andersen and Bollerslev, 1998) to model characteristics of financial time series.

Starting with the pioneering work of Mandelbrot (1963) and Fama (1965), various features of stock returns have been extensively documented in the literature which are important in modeling stock market volatility. It has been found that stock market volatility is time varying and it also exhibits positive serial correlation (volatility clustering). This implies that changes in volatility are non-random. Moreover, the volatility of returns can be characterized as a long-memory process as it tends to persist (Bollerslev, Chou and Kroner, 1992). Schwert (1989) agreed with this argument. Fama (1965) also found the similar evidence. Baillie and Bollerslev (1991) observed that the volatility is predictable in the sense that it is typically higher at the beginning and at the close of trading period. Akgiray (1989) found that GARCH (1, 1) had better explanatory power to predict future volatility in US stock market. Poshakwale and Murinde (2001) modeled volatility in stock markets of Hungary and Poland using daily indexes. They found that GARCH(1,1) accounted for nonlinearity and volatility clustering. Poon and Granger (2003) provided comprehensive review on volatility forecasting. They examined the methodologies and empirical findings of 93 research papers and provided synaptic view of the volatility literature on forecasting. They found that ARCH and GARCH classes of time series models are very useful in measuring and forecasting volatility.

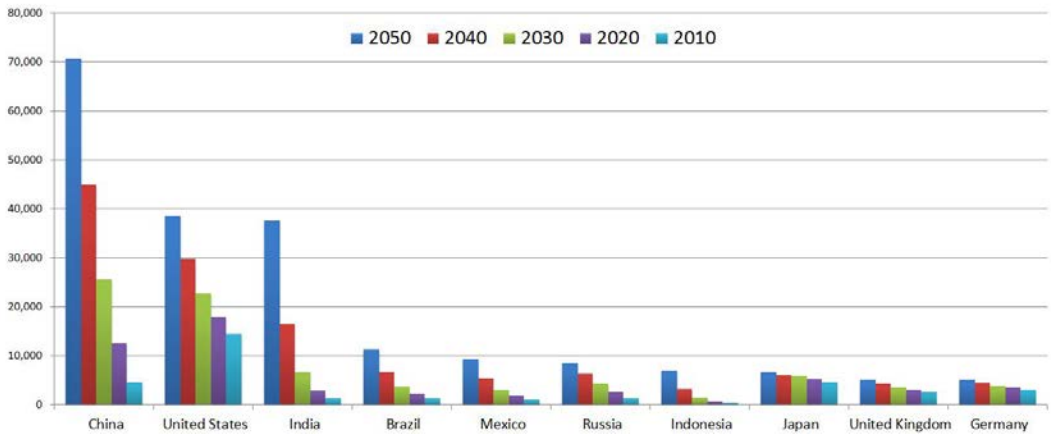
There is relatively less empirical research on stock return volatility in emerging markets. Deregulation and market liberalization measures, rapid development in communication technology and computerized trading systems and increasing activities of multinational corporations have accelerated the growth of capital markets which are now moving

[1] Garner A.C., 1988, Has Stock Market Crash Reduced Customer Spending? Economic Review, Federal Reserve Bank of Kanas City, April, 3-16.

[2] Gertler, M. and Hubbard, R.G.,1989, Factors in Business Fluctuations, Financial Market Volatility, Federal Reserve Bank of Kanas City, 33-72.

towards global financial integration. The growing international integration of financial markets has prompted several empirical studies to examine features of volatility of stock markets across the world. However, we need a more systematic investigation of stock market volatility in emerging stock markets. This paper provides evidence on main features of volatility in the emerging stock markets of BRIC. It is an acronym for Brazil, Russia, India and China. These countries were originally grouped in to BRICs by Goldman Sachs's James O'Neal. BRIC countries are formed because of their crucial role in the today's world economy. The Figure 1 highlights the importance of the BRICs in the world's future economy as they may become the largest economies in the world by 2050 (Glodman Sachs[3]). The economic growth rates for these countries are well above the most of the industrialized countries like USA, Japan,

Figure 1:
Ten Largest Economy of World in 2050, measured in GDP (Billions of 2006 USD)



Source: http://en.wikipedia.org/wiki/File:Top_five_largest_economies_in_2050.jpg

United Kingdom and Canada. During 2002 – 2008, the Chinese economy grew at an average of 10 percent per year while India grew at an average of 8 percent per year (Balakrishnan et el 2009). China also gradually became the world's largest exporter with $1,897 trillion worth of exports (CIA's The Worlds Fact book 2011). Meanwhile, the BRICs are also increasing their trade with one another: especially the Chinese and Indian trade has increased by $60 billion in 2010 while setting a $100 billion bilateral trade target by 2015. The BRICs' large share of foreign exchange reserves in the world economy provides them a strong competitive advantage. All four countries are among the ten largest accumulators of foreign exchange reserves in dollars, accounting for over 40 percent of the world's total ("The trillion Dollar Baby", The Economist Magazine February 2012).

[3] Goldman Sachs : http://www.goldmansachs.com

Moreover, the monetary policy actions of BRICs can influence the rest of the world as they hold a large portion of treasury bonds of many of the foreign countries including the US, UK and Canada. All these above factors make the BRICs highly important in the world economy. So having a better idea about the monetary policy behavior of the BRICs would help other economies to be efficient in their participation in the world economic activities (Tamazian & Chousa, 2009). With the growing importance of BRIC countries in the world economy, it will be instructive to study volatility behavior of their stock markets.

The rest of the paper is organized as follows. Section II provides research design used in the study. Empirical results are discussed in Section III. Section IV summarizes.

II. Research Design

Period of study

We collected data on BOVASPA, RTSI(RTS), Sensex and SSE of Brazil, Russia, India and China's closing price indices respectively from January 1, 2009 to June, 2014. It consists of 1359 observations. The period is the most recent one. These stock markets have become increasingly integrated. The trades between countries have increased. They are playing an important role in the world economy. These might have influenced the behavior and the pattern of volatility and therefore it will be instructive to study volatility in this period.

Methodology

Daily returns are identified as the difference in the natural logarithm of the closing index value for the two consecutive trading days.

Volatility is defined as;

$$\sigma = \sqrt{1/n-1\sum_{t=1}^{n}(R_t - \bar{R})^2} \qquad \text{Equation 1}$$

where $\bar{R}$ = Average return(logarithmic difference) in the sample.

In comparing the performance of linear model with its nonlinear counterparts, we first used ARIMA4 models. Nelson (1990b) explains that the specification of mean equation bears a little impact on ARCH models when estimated in continuous time. Several studies recommend that the results can be extended to discrete time. We follow a classical approach of assuming the first order autoregressive structure for conditional mean as follows:

$$R_t = a_0 + a_1 R_{t-1} + \varepsilon_t \qquad \text{Equation 2}$$

where R_t is a stock return, $a_0 + a_1 R_{t-1}$ is a conditional mean and ε_t is the error term in period t.

[4] A process that combines Autoregressive process (AR) and Moving Average terms (MA) terms. AR process where the present observations depend on the previous observations and MA is a weighted average of the present and the recent past observations of a process.

The error term is further defined as:

$$\varepsilon_t = \upsilon_t \sigma_t \qquad \text{Equation 3}$$

where υ_t is white noise process that is independent of past realizations of ε_{t-i}. It has zero mean and standard deviation of one. In the context of Box and Jenkins (1976), the series should be stationary before ARIMA models are used. Therefore, Augmented Dickey Fuller test (ADF) is used to test for stationarity of the return series. It is a test for detecting the presence of stationarity in the series. The early and pioneering work on testing for a unit root in time series was done by Dickey and Fuller (1979 and 1981). If the variables in the regression model are not stationary, then it can be shown that the standard assumptions for asymptotic analysis will not be valid. ADF tests for a unit root in the univariate representation of time series. For a return series R_t, the ADF test consists of a regression of the first difference of the series against the series lagged k times as follows:

$$\Delta r_t = \alpha + \delta r_{t-1} + \sum_{i=1}^{p} \beta_i \Delta r_{t-i} + \varepsilon_t \qquad \text{Equation 4}$$

$$\Delta r_t = r_t - r_{t-1}; r_t = \ln(R_t)$$

The null hypothesis is H_0: $\delta = 0$ and H_1: $\delta < 1$. The acceptance of null hypothesis implies non-stationarity. We can transform the non-stationary time series to stationary time series either by differencing or by detrending. The transformation depends upon whether the series is difference stationary or trend stationary.

One needs to specify the form of the second moment, variance, σ_t^2 for estimation. ARCH and GARCH models assume conditional heteroscedasticity with homoscedastic unconditional error variance. That is, the changes in variance are a function of the realizations of preceding errors and these changes represent temporary and random departure from a constant unconditional variance. The advantage of GARCH model is that it captures the tendency in financial data for volatility clustering. It, therefore, enables us to make the connection between information and volatility explicit since any change in the rate of information arrival to the market will change the volatility in the market.

In empirical applications, it is often difficult to estimate models with large number of parameters, say ARCH (q). To circumvent this problem, Bollerslev (1986) proposed GARCH (p, q) models. The conditional variance of the GARCH (p,q) process is specified as

$$h_t = \alpha_0 + \sum_{j=1}^{q} \alpha_j \varepsilon_{t-j}{}^2 + \sum_{i=1}^{p} \beta_i h_{t-i} \qquad \text{Equation 5}$$

with $\alpha_0>0$, α_1, α_2,………… $\alpha_q \geq 0$ and β_1, β_2, β_3,........, $\beta_p \geq 0$ to ensure that conditional variance is positive. In GARCH process, unexpected returns of the same magnitude (irrespective of their sign) produce same amount of volatility. The large GARCH lag coefficients β_i indicate that shocks to conditional variance takes a long time to die out, so volatility is 'persistent.' Large GARCH error coefficient α_j means that volatility reacts quite intensely to market movements and so if α_j is relatively high and β_i is relatively low, then volatilities tend to be 'spiky'. If $(\alpha + \beta)$ is close to unity, then a shock at time t will persist for many future periods. A high value of it implies a 'long memory.' The model is then tested for ARCH effect using ARCH-LM test to judge model adequacy. If ARCH-LM test results are statistically insignificant, the model will be adequate.

III. Empirical Results

The descriptive statistics for the return series include mean, standard deviation, skewness, kurtosis, Jarque-Bera and Ljung Box. ARCH-LM statistics are also exhibited in the Table 1.

Table 1: Descriptive Statistics of Daily Returns

Statistic	Bovaspa	RTS	Sensex	SSE
Mean	0.00021	0.00055	0.00071	0.00006
Standard deviation	0.01483	0.01985	0.01342	0.01333
Skewness	-0.05348	-0.20030	1.14196	-0.37298
Kurtosis	4.94187	6.63919	18.95906	5.46130
Jarque-Bera Statistics	241.01(0.000)	758.45(0.000)	14706.5(0.000)	374.27(0.000)
$Q^2(12)$	167.73(0.000)	207.46(0.000)	62.96(0.000)	201.78(0.000)
ARCH LM statistics (at Lag =1)	12.43(0.000)	28.58(0.000)	1.09(0.29)	3.15(0.076)
ARCH LM statistics (at Lag =5)	75.41(0.000)	67.82(0.000)	11.59(0.041)	55.35(0.000)

Notes: ARCH LM statistic is the Lagrange multiplier test statistic for the presence of ARCH effect. Under null hypothesis of no heteroscedasticity, it is distributed as $\lambda^2(k)$. *$Q^2(K)$ is the Ljung Box statistic identifying the presence of autocorrelation in the squared returns. Under the null hypothesis of no autocorrelation, it is distributed as* $\lambda^2(k)$.

The mean returns for all the stock indices are very close to zero indicating that the series are mean reverting. The return distribution is negatively skewed, indicating that the distribution is non-symmetric. Large value of Kurtosis suggests that the underlying data are leptokurtic or thick tailed and sharply peaked about the mean when compared with the normal distribution. Since GARCH model can feature this property of leptokurtosis evidence in the data.

The Jarque-Bera[5] statistics calculated and reported in the Table-1 to test the assumption of normality. The results show that the null hypothesis of normality in case of all the stock markets is rejected.

The Ljung-Box LB^2 (12) statistical values of all the series respectively rejects significantly the zero correlation null hypothesis. It suggests that there is a clustering of variance. Thus, the distribution of square returns depends on current square returns as well as several periods' square returns, which will result in volatility clustering.

[5] The B-J teat statistic is T[skewness^2/6+(kurtosis-3)^2/24].

Stationary condition of all the BRIC stock markets' daily return series were tested by Augmented Dickey-Fuller Test (ADF). The results of this test are reported in the Table 2.

Table 2: Unit Root Testing of Daily Returns: Augmented Dickey-Fuller Test

Null Hypothesis	Test statistics								Mackinnon Asymptotic
Presence of Unit root	Level				First Difference				Critical value @ 1% level
	Bovaspa	RTS	Sensex	SSE	Bovaspa	RTS	Sensex	SSE	
Intercept	-2.97(0.08)	-2.73(0.08)	-2.25(0.18)	-1.89(0.34)	-38.21(0.00)	-33.38(0.00)	-34.60(0.00)	-36.53(0.00)	-3.44
Trend &Intercept	-3.00(0.13)	-2.67(0.25)	-2.25(0.30)	-4.25*(0.064)	-38.25(0.00)	-33.45(0.00)	-34.59(0.00)	36.59(0.00	-3.97
Trend coefficient	-0.00 (0.06)	-0.00(0.43)	0.00(0.17)	-0.00(0.00)	-0.00(0.18)	-0.00(0.08)	-0.00(0.62	-0.00(0.12)	
None	0.47(0.81)	0.82(0.89)	1.89(0.99)	0.12(0.72)	-38.22(0.00)	-33.36(0.00)	-34.53(0.00)	-36.55(0.00)	-2.57

ADF statistics in level series shows presence of unit root in all the stock markets as their Mackinnon's value do not exceed the critical value at 1% level. It suggests that the price series are non-stationary. The trend coefficients of the series are statistically insignificant suggesting absence of any trend in the markets. It is, therefore, necessary to transform the series to make it stationary by taking its first difference. ADF statistics reported in the Table 2 show that the null hypothesis of a unit root in case of all stock indices is rejected. The absolute computed values for the indices are higher than the MacKinnon critical value at 1% level. Thus, the results of the indices show that the first difference series are stationary.

Nonlinearity in the series is analyzed using BDSL test. The BDSL (Brock,Dechert, Scheinkman and LeBaron, 1996) test is a nonparametric test with the null hypothesis that a time series is independent and identically distributed. The alternative hypothesis includes both deterministic chaos as well as linear and nonlinear stochastic behaviour. It measures the statistical significance of the correlation dimension calculations. The correlation integral is the probability that any two points are within a certain length, 'e' apart in phase space. The correlation integrals are calculated according to equation 6.

$$C_m(e) = (1/N^2) \times \sum_{I,J=1}^{T} Z(e - |X_i - X_j|), i \neq j, \qquad \text{Equation 6}$$

where Z(e)=1 if $e - |X_i - X_j|$ >0, 0 otherwise. T= number of observations, e=distance, C_m =correlation integral for dimension m, N= length of the series, X_i, X_j=the index series.

The function Z in the equation3 counts the number of points within a distance 'e' of one another. The correlation integral calculates the probability that two points that are part of two trajectories in phase space are 'e' units apart. The BDS statistics, W, is given by

$$W_N(e,T) = \left| C_n(e,T) - C_l(e,T)^N \right| \times \sqrt{T / S_N(e,T)} \qquad \text{Equation 7}$$

where $S_N\left(e,T\right)$ is the standard deviation of the correlation integrals. The test is able to locate many types of nonlinearity, nonstationarity and deterministic chaos. The null hypothesis is rejected with 95% and 99% confidence when W exceeds 1.96 and 3 respectively. If null hypothesis is rejected, we can say that the time series is nonlinear or has chaotic behavior.

Table 3: BDS test statistic for residuals from ARIMA(1,0) Model

M	bovaspa	rrts	sensex	sse
2	0.122	4.845	4.726	-0.179
3	2.111	7.101	6.739	0.531
4	3.433	8.536	8.162	0.922
5	3.956	9.713	9.533	0.851
6	3.945	11.378	11.599	1.143
7	4.184	13.466	13.814	1.255
8	3.921	15.468	15.780	0.904
9	3.627	17.736	19.097	1.548
10	2.992	19.443	20.515	0.980
2	0.691	5.394	5.487	0.753
3	2.800	8.190	7.616	1.745
4	4.103	9.830	9.032	1.969
5	5.035	11.205	10.414	1.812
6	5.802	12.797	11.793	1.841
7	6.540	14.396	13.523	1.853
8	7.298	16.378	15.310	1.815
9	8.034	18.562	17.357	1.633
10	8.842	20.983	19.779	1.684
2	1.646	5.089	5.610	1.584
3	3.668	7.722	7.662	2.913
4	5.035	9.392	9.362	3.273
5	6.083	10.747	10.769	3.262
6	7.001	12.286	11.989	3.392
7	7.841	13.497	13.281	3.628
8	8.555	14.852	14.471	3.853
9	9.268	16.393	15.707	3.886
10	9.982	17.905	16.921	4.034
2	2.349	4.803	5.558	1.873
3	4.450	6.724	7.463	3.337
4	5.832	8.345	9.287	4.023
5	6.887	9.575	10.704	4.181
6	7.791	11.012	11.792	4.449
7	8.564	12.050	12.905	4.789
8	9.262	13.065	13.931	5.126
9	9.878	14.144	14.842	5.262
10	10.534	15.068	15.656	5.435

Note: Marginal significance level of the statistics for a two tailed test is 1.96

The BDSL test is applied to the residuals of ARMA(1,0) models in the stock markets and used embedding dimensions of 2 to 10 and epsilons(e) ranging from half to two standard deviations. The results in Table 3 indicate significant BDSL statistics for all the stock indices, suggesting the presence of nonlinearity. It suggests that ARMA(1,0) model fails to capture nonlinearity in the data.

To test for heteroscedasticity, the ARCH-LM test is applied to residuals of ARIMA (1,0) equation. The results are reported in Table 1. The ARCH-LM test at lag length 1 and 5 indicate presence of ARCH effect in the residuals in the stock markets. It implies clustering of volatility where large changes tend to be followed by large changes, of either sign and small changes tend to be followed by small changes (Engle, 1982 and Bollerslev, 1986). To explore the nature of volatility, GARCH (1,1) model is applied in the stock markets. The results of the estimated model are reported in Table 4. The GARCH model is tested for their fitness and adequacy using ARCH-LM test. The results are also presented in the Table 4. The findings indicate that there is no ARCH effect left after estimating the models because the results of ARCH-LM test statistics at lag length 5 reported in the Table 4 are statistically insignificant as its probability value is higher than 0.05. It, therefore, suggests that the estimated models are better fit and successfully account for time varying volatility.

Table 4: Coefficients of GARCH model

	Bovaspa	RTS	Sensex	SSE
Coefficients	GARCH(1,1)	GARCH(1,1)	GARCH(1,1)	GARCH(1,1)
α_0	0.000(0.000)	0.000(0.000)	0.000(0.000)	0.000(0.005)
α_1	0.060(0.000)	0.058(0.000)	0.053(0.000)	0.031(0.000)
β_1	0.910(0.000)	0.925(0.000)	0.936(0.000)	0.952(0.000)
$\alpha_1+\beta_1$	0.970	0.983	0.989	0.983
ARCH-LM test	15.20(0.12)	2.83(0.98)	4.75(0.91)	13.99(0.12)

Note: Figures in the parenthesis indicate probability Value.

The parameters estimates of the GARCH (1, 1) models in Tables 4 are all statistically significant. The estimates of β_1 are always markedly greater than those of α_1 and the sum $\alpha_1+\beta_1$ is very close to but smaller than unity. It is observed that $\alpha_1+\beta_1$ is equal to 0.970 for Bovaspa, 0.983 for RTS, 0.989 for Sensex and 0.983for SSE. This is less than unity indicating stationary condition is not violated. The sum of Indian stock market is highest followed by Chinese stock market. It indicates a long persistence of shocks in volatility in Sensex. As the lag coefficient of conditional variance β_1 is higher than the error coefficient α_1 implying that volatility is not spiky in all the stock markets. It also indicates that the volatility does not decay speedily and tends to die out slowly.

Table 5: BDS test statistic for residuals from GARCH(1,1) Model

m	bovaspa	rrts	sensex	sse
2	-1.592	-1.289	-1.867	-1.938
3	-1.578	-1.365	-1.500	-1.745
4	-1.148	-1.568	-1.625	-1.663
5	-0.651	-1.736	-1.805	-1.707
6	-1.023	-1.422	-2.133	-1.735
7	-1.310	-1.482	-1.294	-1.681
8	-1.851	-0.718	-0.908	-1.548
9	-1.847	-0.913	-1.197	-2.431
10	-1.871	-4.030	-1.614	-2.862
2	-2.786	-1.501	-1.810	-1.913
3	-2.115	-1.383	-1.628	-1.598
4	-1.934	-1.332	-1.399	-1.748
5	-1.665	-1.363	-0.985	-1.833
6	-1.524	-1.121	-0.827	-1.950
7	-1.324	-0.988	-0.567	-1.948
8	-1.029	-0.749	-0.391	-1.858
9	-0.782	-0.504	-0.225	-1.824
10	-0.387	-0.440	-0.270	-1.670
2	-2.358	-1.501	-1.848	-1.773
3	-1.757	-1.383	-1.796	-1.316
4	-1.673	-1.332	-1.558	-1.516
5	-1.507	-1.363	-1.087	-1.014
6	-1.368	-1.121	-0.909	-1.088
7	-1.211	-0.988	-0.545	-1.863
8	-1.103	-0.749	-0.322	-1.990
9	-0.963	-0.504	-0.108	-1.850
10	-0.821	-0.440	0.029	-1.858
2	-1.331	-1.303	-1.612	-1.038
3	-0.729	-1.514	-1.706	-0.570
4	-0.778	-1.478	-1.591	-0.640
5	-0.732	-1.464	-1.132	-1.070
6	-0.639	-1.234	-0.942	-1.144
7	-0.512	-1.228	-0.582	-1.083
8	-0.420	-1.038	-0.342	-0.960
9	-0.296	-0.852	-0.114	-0.982
10	-0.159	-0.814	-0.002	-0.972

Note: Marginal significance level of the statistics for a two tailed test is 1.96.

The residuals from GARCH(1,1) process are tested for nonlinearity using the BDSL test. The results are reported in Table 5. It suggests that the nonlinearity is not present in the residuals. It indicates that the nonlinearity occurs due to volatility clustering is successfully captured by the GARCH model.

IV. Summary

The volatility in the BRIC stock markets exhibits the persistence of volatility, mean reverting behavior and volatility clustering. The study used more than five years of recent daily data on BRIC stock indices to illustrate these stylized facts, and the ability of GARCH(1,1) to capture these characteristics. Daily returns in the stock markets exhibit nonlinearity and volatility clustering which are satisfactorily captured by the GARCH models. In all the stock markets, volatility tends to die out slowly. Results suggest that the volatility is more persistent in the Indian stock market than the other stock markets.

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