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Volatility Behaviour in Emerging Stock Markets – A GARCH Approach

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Abstract

This study primarily focuses on three aspects - (i) volatility in the emerging stock markets across globe by application of GARCH family models, (ii) study of ARMA structures, and (iii) a comparison of symmetric and asymmetric volatility. In the last decade or so, investors from developed countries are mostly focusing on the emerging economics as their investment opportunities. They associate a good amount of risk premium with these countries as far as the risk and return are concerned with their investments. Investments drawn from developed nations seems to make stock markets of emerging nations more volatile as these investment are exposed to both irrational and rational factors. Hence it's imperative to understand the volatility behaviour of emerging stock markets over a period of time and also to study the comparative analysis of the volatility behaviours' across these markets. This draws us to revisit the topic on volatility behaviour considering the emerging markets for this study. In this paper an attempt is being made to estimate the volatility behaviour of stock markets of 10 emerging economics and hence concentrated on India, China, Indonesia, Sri Lanka, Pakistan, Russia, Brazil, South Korea, Mexico, and Hong Kong.

Keywords: Stock Market Volatility, GARCH, Emerging Markets, Heteroscedasticity, ARMA

JEL Classification: - G1, G10, G18, G19

Introduction

Stock market volatility has always received a lot of attention in the empirical literatures; however research on this topic still has the potential to explore new information. Hence this study is an attempt to explore the volatility pattern of ten emerging markets selected on the basis of their listing as emerging economics. Investors, regulators, and other stakeholders always keep an eye on the volatility of different stock markets to draw their decisions. A lot of volatility had been witnessed during the phase of global economics crisis during 2008-09 and Euro Zone debt crisis during 2010-13. This study thereby given emphasis on these two periods and hence considered a total period of almost eleven years (2003-2014) to estimate the volatility of the countries considered for this study.

Literature Review

Yang and Liu (2012) studied the forecasting power volatility index in emerging economics particularly in reference to Taiwan market and found that the volatility index(TVIX) of Taiwan stock index options is a strong indicator of future stock market volatility. The TVIX outperforms the historical volatility and the GARCH volatility forecast in assessing the activities of Taiwan's stock market. Kiymaz and Girard (2009) studied stock market volatility and trading volume in emerging market and found that persistency of conditional volatility is high and very close to unity, implying that current information can be used to predict future volatility. Unexpected news doesn't affect volatility significantly but the forecastability of volume activity is high. Franses and Dijk (1996) forecasted stock market volatility using (nonlinear) GARCH model and as per their findings the Q GARCH model is best when the estimation sample does not content extreme observations such as the 1987 stock market crash and the GJR model cannot be recommended for forecasting. For their estimation of volatility they used 'within sample estimation' and 'out of sample estimation' and found that the forecasting performance of the GARCH type models appears sensitive to extreme within-sample observations. Gulen and Mayhem (2000) studied stock

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Table 1: Emerging Stock Market at Glance

Country	Name of Exchange	Index	Year of Establishment	Market Capitalisation	Index Calculation Methodology	No of Companies Lists
India	Bombay Stock Exchange	Sensex	1875	USD 1.32 Trillion as of January 2013	Free-Float Market Capitalisation	5000+
China	Shanghai Stock Exchange	SSE Composite	1990	USD 2.3 trillion (2011)	Free-Float Market Capitalisation	998+
Brazil	IBOVESPA	IBOVESPA	1890	USD 1.22 Trillion (2012)	NA	365
Pakistan	Karachi Stock Exchange	KSE 100	1947	USD 53.3 billion May 2013	NA	652
Srilanka	Colombo Stock Exchange	ASPI	1985	LKR 2.3 Trillion	Weighted Market Capitalisation	289
Mexico	Mexican Stock Exchange	IPC	1933	USD 460.4 billion	Weighted Market Capitalisation	466
Russia	Moscow Exchange	RTS	1995	USD 13.5 billion	Free Float Market Capitalisation	1845
South Korea	Korea Stock Exchange	KOSPI	1960	USD 1.1 trillion	Weighted free float market Capitalisation	773
Indonesia	Jakarta Stock Exchange	JSKE	1912	USD 426.78	Modified Weighted Capitalisation	462
Hong Kong	HongKong Stock Exchange	HSI	1891	HK$16.985 trillion (Nov 2011	Free Float Capitalisation	1421

index futures trading and volatility in international equity markets and found that symmetric GARCH and GJR GARCH perform marginally better than others. United States and Japan's volatility may have increased after listing of stock index, but for other countries volatility decreased or stayed roughly the same. In most of the other cases, volatility tends to be lower in periods when open interest in stock index future is high, but in case of United States and Japan there is an opposite result. Mala and Reddy (2007) measured stock market volatility in an emerging economy and the study observed that seven out of the sixteen firms listed in Fiji's stock market are volatile. It is further found that change in the interest rates have significant effect on stock market volatility. The finding further suggests that the volatile firms are exposed to government regulations, where the liquidity has been low over the years. Jayasuriya, Shambora and Rossiter (2009) studied asymmetric volatility in emerging and mature markets and the empirical results of the study suggest that descriptive statistics for the sample data shows higher standard deviation for emerging markets in comparison to the mature markets. First sub-period shows high α for emerging markets indicating that emerging markets often react somewhat more to news in comparison to the mature markets.Whereas, second sub-period shows asymmetric volatility for both mature and emerging markets. And, in the third sub-period each of the mature markets exhibits asymmetric volatility as do the emerging markets with the exception of Philippines. Wei (2002) forecasted stock market volatility with non-linear GARCH models for China and the results of the study suggest that GARCH (1,1) model is preferred within the sample period i.e., from 1992 to 1996 to QGARCH and GJR GARCH models whereas, the QGARCH model is found appropriate in case for forecasting out of the sample i.e., for 1997 and 1998. McMillan and Alan (2003) studied asymmetric volatility dynamics in high frequency FTSE-100 stock index futures and the results suggest that a high kurtosis, both positive and negative skewness, and series is not normally distributed as confirmed by Jarque-Bera test. GARCH effect is in the data at all frequencies that has been confirmed by ARCH-LM test. TGARCH (1,2,1) models, the positive coefficients obtained, indicate negative shocks increase volatility by a greater magnitude than positive shocks of equal size. QGARCH form suggests that predictive asymmetry is of second order form, though this effect is statistically insignificant in returns data, whereas, QGARCH-M form yields no evidence of a statistically significant effect of volatility on returns at either hourly or quarter-hourly frequency and therefore, no evidence of nay volatility feedback through the interaction of predictive asymmetry and risk premium is found. Floros (2008) studied volatility using GARCH models in Egypt and Israel markets and found that the coefficient of the lagged squared return is positive and statistically significant for most specifications and witnessed a strong GARCH effect for both financial markets. The coefficient of lagged conditional variance is significantly positive and less than one, indicating that the impact of old news on volatility is significant and magnitude of the coefficient β is especially high for TASE-100 index, indicating memory in the variance. Mean equation of GARCH-M model, denoted by β_2 is positive but insignificant for both indices, suggesting that higher market-wide risk, proxied by the conditional variance, will not necessarily lead to higher returns. EGARCH models show a negative and significant γ parameter for both indices, indicating the existence of the leverage effect in returns during sample period.

Methodology and Research design

The methodology under this study is divided into the following areas.

1. Data and samples
2. Hypothesis
3. Tools and techniques

Data and Samples

Close level data for this study are collected for ten emerging economies including India. However South Africa and Turkey are not included for the lack of availability of data. All the main indices are included for all the ten countries and the data are collected from yahoo finance website i.e. *in.finance.yahoo.com*. The details regarding the data are incorporated in Table 2.

The closing level data collected are converted into continuously compounded return by applying the following formula

Table 2: Data and Samples

Country	*Name of Stock Exchange*	*Name of the Index*	*Period Of Study*	*No of Observation*	*Data Type*
India	Bombay Stock Exchange	BSE Sensex	01.04.2003-29.08.2014	2904	Closing Level Data
China	Shanghai Stock Exchange	SSEC- Shanghai Composite	01.04.2003-29.08.2014	2817	Closing Level Data
Indonesia	Indonesia Stock Exchange (Bursa Efek Indonesia)	JKSE- Jakarta Composite	01.04.2003-29.08.2014	2841	Closing Level Data
Sri Lanka	Colombo Stock Exchange	All share price index (ASPI)	01.04.2003-29.08.2014	2810	Closing Level Data
Pakistan	Karachi Stock Exchange	KSE 100	01.04.2003-29.08.2014	2837	Closing Level Data
Russia	Moscow Exchange	RTS Index	01.04.2003-29.08.2014	2876	Closing Level Data
Brazil	Brazil Stock Exchange (IBOVESPA)	IBOVESPA	01.04.2003-29.08.2014	2861	Closing Level Data
South Korea	Korea Stoc Exchange	KOSPI	01.04.2003-29.08.2014	2889	Closing Level Data
Mexico	Mexican Stock Exchange (Bolsa Mexicana de Valores)	IPC	01.04.2003-29.08.2014	2837	Closing Level Data
Hong Kong	Hong Kong Stock Exchange	HSI - Hang Seng Index	01.04.2003-29.08.2014	2867	Closing Level Data

$$r_t = \ln(P_t / P_{t-1}) * 100 \tag{1}$$

Where $r_{t =}$ logarithmic index return; ln = natural logarithm; P_t = current closing price; P_{t-1} = previous closing price

Hypothesis Testing

The following null hypotheses are being formulated for this study:

H_0: The return data of all the indices are normally distributed

H_0: Volatilities in BRIC countries are more in comparison to developing nations.

H_0: Recent information has more impact on the volatility than the old news

H_0: Asymmetric information impacts more on the volatility of Emerging markets

Tools and Techniques

Normality Test

The data distribution is said to be normal if its skewness is zero and kurtosis is three. The descriptive statistics like mean, standard deviation skewness, and kurtosis of the return data over the period study are calculated by using a statistical software package called E views-7.1. The normality test of the descriptive statistics is carried on by using an asymptotic Jarque-Bera (1981) test statistic. The formula of Jarque-Bera (JB) statistics is stated below:

$$\text{JB Statistics} = T\left(\frac{S^2}{6} + \frac{(k-3)^2}{24}\right) \tag{2}$$

where T = No. of observations

S = Skewness coefficient

K = Kurtosis coefficient

JB test of normality is the test of the joint null hypothesis if S & K are 'O' and 3, respectively.

Stationarity Test

The financial time series data is called stationary if its mean, variance, and auto-covariance at different lags are same and so time independent. For a stationary series, stocks to the system die away gradually. If the effect of the stocks to the system persists for a longer period, the system will be explosive due to the stock. If the data would not be stationary, no study can be done as non-stationary data lead to spurious regression. The study has therefore conducted stationarity test on the data by using the Augmented Dickey Fuller (1976) test which is stated below:

$$\text{ADF test statistics } \Delta Y_t = \beta_1 + \beta_2 t + \delta Y_{t-1} + \sum_{i=1}^{m} \alpha_i \Delta Y_{t-i} + \epsilon_t \tag{3}$$

Heteroscedasticity Test

Heteroscedasticity refers to the unequal variance $\left(\sigma_t^2\right)$ in the error term (ut) obtained from the regression of Y_t with Y_{t-I} under Ordinary Least Square (OLS) method. In other words, if the coefficient of Y_{t-1} is statistically significant, it indicates the presence of autocorrelation in the return series between Y_t and Y_{t-1}. In the presence of heteroscedasticity, if Classical Linear Regression Method is applied, the best Linear Unbiased Estimates (BLUE) will not be obtained. Hence, the study here intends to develop volatility models under the presence of heteroscedasticity.

In order to known the number of autoregressive (AR), moving average (MA), and ARMA terms, the data of Sensex and Nifty have been tested for period of study by using Box and Jenkins (1976) methodology and Ljung-Box (1978) test.

Box and Jenkins (1976) Methodology

Box-Jenkins (1976) methodology involves three steps:

1. Identification of AR/MA/ ARMA and ARIMA order by correlogram and partial correlogram.
2. Estimation of the parameters (coefficients) of the AR/MA/ARMA and ARIMA model
3. Diagnostic checking of the selected AR/MA/ ARMA/ARIMA model to see that the model selected fits the data reasonably well.

Under this methodology, the study has calculated autocorrelation (AC) and partial autocorrelation (PAC) at various lags from 1 to 30 of the u_t obtained from the OLS of Y_t and Y_{t-1}.

AC at k lag (ρ_k) = Covu$_t$, u$_{t-k}$ / $\sqrt{Varu_t \times Varu_{t-k}}$ (4)

PAC at lag 1 = Ac at lag1 = $\left(\rho_{11} = \rho_1^2\right)$ (5)

PAC at lag2 $\left(\rho_{22}\right) = \left(\rho_2 - \rho_1^2\right) \big/ \left(1 - \rho_1^2\right)$ (6)

The ACs and PACs obtained above are plotted against different lags graphically and the graph so obtained is called correlogram. From this type of visual inspection of a correlogram tentative AR/MA/ARMA model could be determined.

Then as per the Box-Jenkin's methodology, in order to precisely determine the AR/MA/ARMA terms, OLS regression is run on Y_t with Y_{t-I} and u_{t-1} and parameters are noted down. In order to know the significance of regression coefficients i.e. regression coefficients of lagged term, Akaike's Information Criteria (AIC) and Schwarz's Bayesian Information Criteria (SBIC) are applied. The formula used for AIC and SBIC are stated below:

AIC Value = $T\left[l_n\left(\sum_{t=1}^{T} u_t^2\right)\right] + 2k$ (7)

SBIC Value = $T\left[l_n\left(\sum_{t=1}^{T} u_t^2\right)\right] + k\ln(T)$ (8)

where,

K = No. of parameters to be estimated

T = total No. of Observations

ln = Natural logarithm

Ljung-Box (1978) test

The significance test of the values of (AC) and (PAC) are done by the Q-Statistics developed by Ljung-Box (1978). The formula for Q-Statistics is given below:

$$Q_m = T(T+2)\sum_{i=1}^{m} \frac{\rho_i^2}{m-1} \approx x_m^2 \quad (9)$$

Q_m = Ljung-Box Q statistics

T = No. of observations

i = No. of lags varies from 1, 2, ……., m.

ρ_m^2 = Sample ac at lag m

x_m^2 = chi-square distribution 'm' degrees of freedom.

Volatility Modeling

The study has taken care of calculating the volatility of all the indices over the period of study by recognising the characteristics of the stock market data like heteroscedasticity, clustering, asymmetry and persistence. The study by using AR and MA terms under Box-Jenkins (1976) and Ljung-Box (1978) has developed the ARMS model for the calculation of volatility of Sensex and Nifty.

The Auto Regressive Conditional Heteroscedasticity (ARCH) developed by Engle (1982) has been used to estimate the conditional variance under the presence of heteroscedasticity. Bollerslev (1986) developed a model which considers a combination of squared residuals at lag 'q' and conditional variance at lag 'p' and the model is named as Generalised ARCH or GARCH (q, p) model. There are several extensions of GARCH models which calculate conditional variance in the presence of asymmetric nature of shocks and persistence features of the shocks to the market.

To capture the asymmetric effect of news, Nelson (1991) proposed EGARCH model for the estimation of conditional volatility and hence used in this study to capture the asymmetric volatility of all the indices.

$\sigma^2_t = \alpha_0 + \alpha_1 u^2_{t-1} + \alpha_2 u^2_{t-2} + \ldots\ldots\ldots + \alpha_q u^2_{t-q}$ ……………… ARCH (q) (10)

where α_0 = is the measure of long term constant volatility i.e. unconditional variance estimation.

$\alpha_1 \ldots \alpha_q$ are the coefficients of the residuals / error terms

α_1= is the measure of persistence – reflects the tendency of the volatility of share or index being affected by previous day.

$\sigma^2_t = \alpha_0 + \alpha_1 u^2_{t-1} + \beta\, \sigma^2_{t-1}$ GARCH (1,1) (11)

where α_0, α_1 and β_1 are the coefficients of the regression

α_0 is the measure of long term constant volatility i.e. unconditional variance estimation.

$\alpha_1 + \beta_1$ represents persistence- tendency of an index being affected by the previous days' volatility

α_1 is the coefficient of the squared error term of the previous day, describes volatility due to one day old news.

β_1 is the coefficient of the lagged conditional variance and describes the volatility due to news which are old by more than one day.

$$\ln(\sigma^2{}_t) = \alpha_0 + \alpha_1\left[\frac{|u_{t-1}|}{\sqrt{\sigma^2_{t-1}}} - \sqrt{\frac{2}{\pi}}\right] + \gamma\frac{u_{t-1}}{\sqrt{\sigma^2_{t-1}}} + \beta\ln(\sigma^2_{t-1})$$

EGARCH(1,1) **(12)**

1. The equation for the conditional variance is in log-linear form. Regardless of magnitude of ln ($\sigma_t{}^2$), the implied value of $\sigma_t{}^2$ can never be negative. Hence, it is permissible for the coefficients to be negative.
2. Instead of using the value of $u^2{}_{t-1}$, EGARCH model uses the level of standardized value of u_{t-1} [i.e. $\frac{u_{t-1}}{\sqrt{\sigma^2_{t-1}}}$]. Nelson argues that this standardisation allows for a more natural interpretation of the size and persistence of shocks. After all, the standardised value of u_{t-1} is a unit-free measure.
3. The EGARCH model allows for leverage effects. If $\frac{u_{t-1}}{\sqrt{\sigma^2_{t-1}}}$ is positive, the effect of the shock on the log of the conditional variance is $\alpha_1+\gamma_1$. If $\frac{u_{t-1}}{\sqrt{\sigma^2_{t-1}}}$ is negative, the effect of the shock on the log of the conditional variance is $-\alpha_1+\gamma_1$.

Table 3: Descriptive Statistics of India

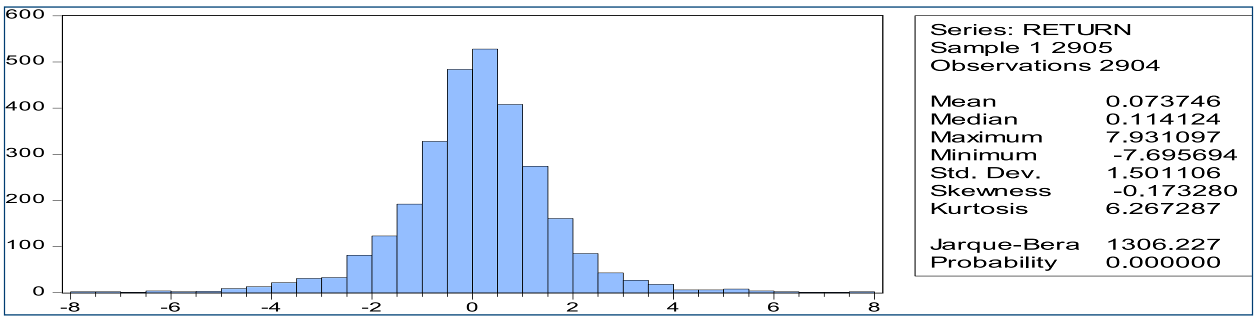


Table 4: Descriptive Statistics of Brazil

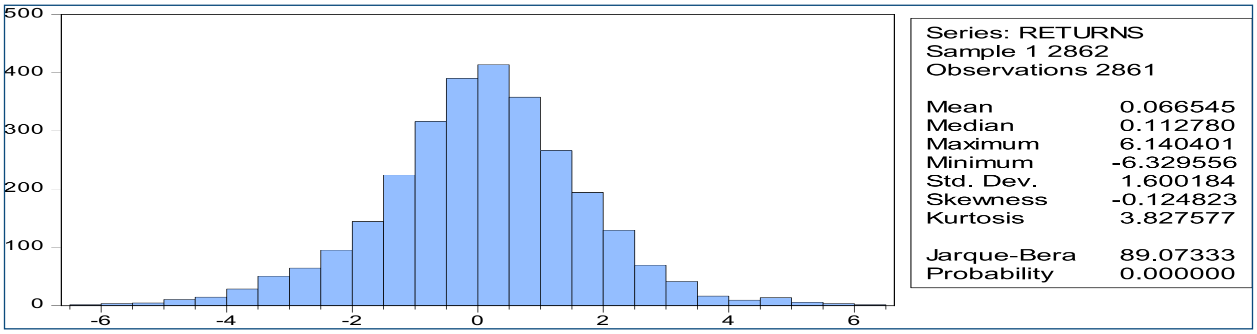


Table 5: Descriptive Statistics of Srilanka

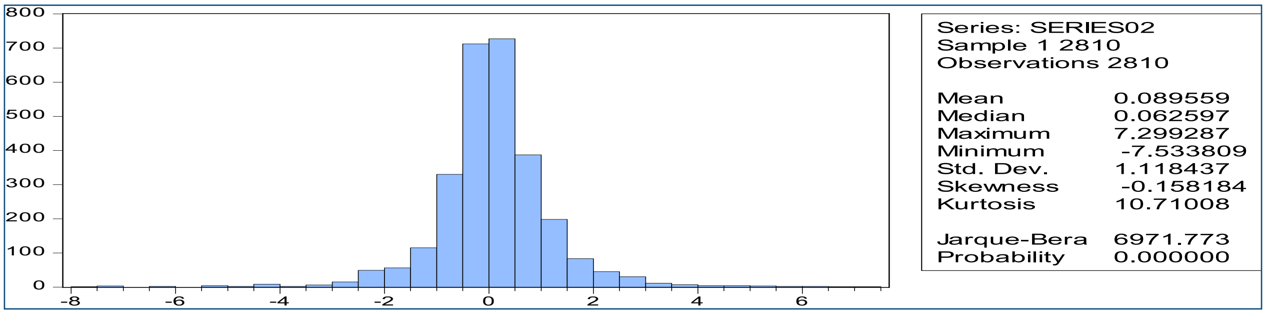


Table 6: Descriptive Statistics of HongKong

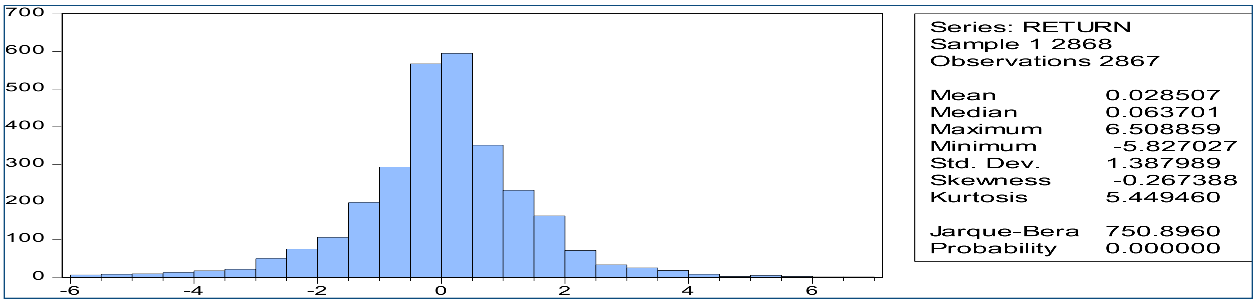


Table 7: Descriptive Statistics of Indonesia

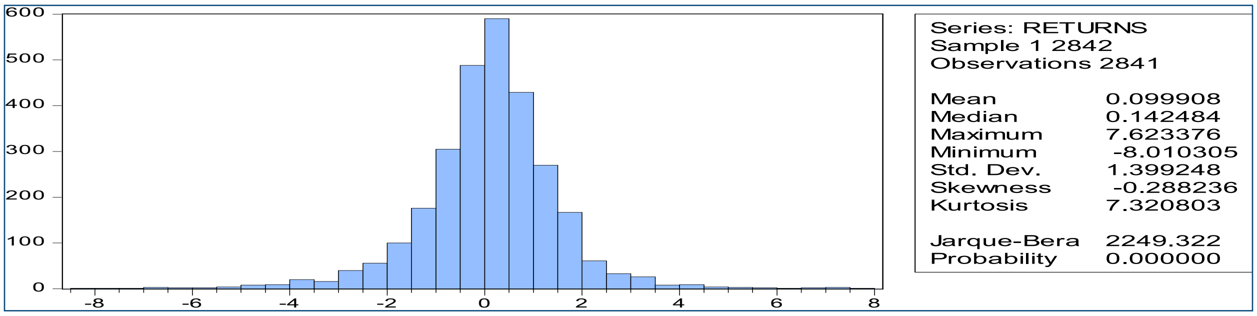


Table 8: Descriptive Statistics of Pakitan

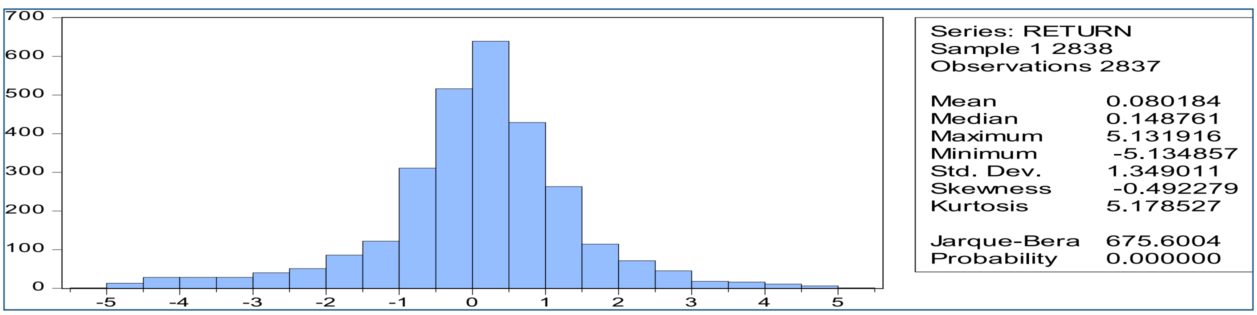


Table 9: Descriptive Statistics of Mexico

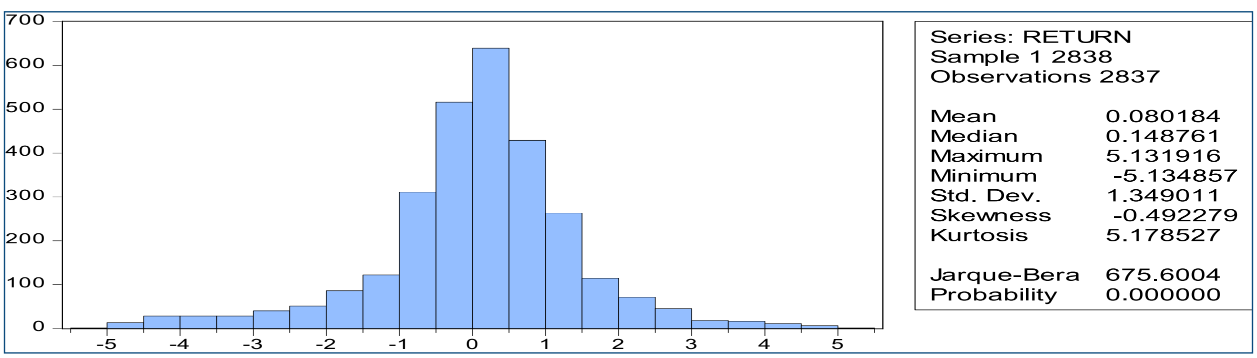


Table 10: Descriptive Statistics of South Korea

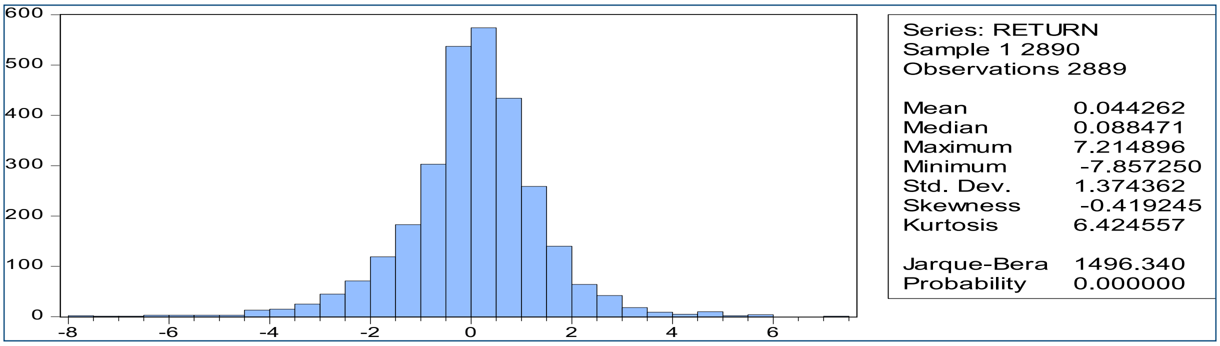


Table 11: Descriptive Statistics of China

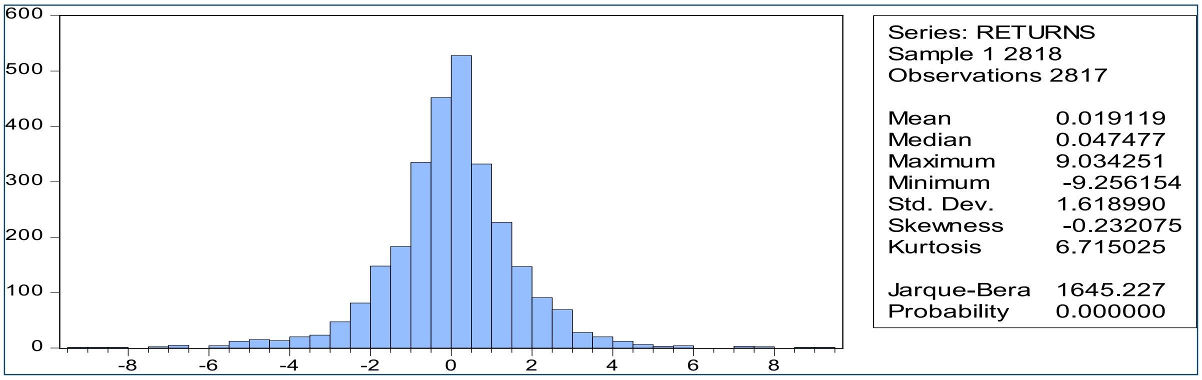
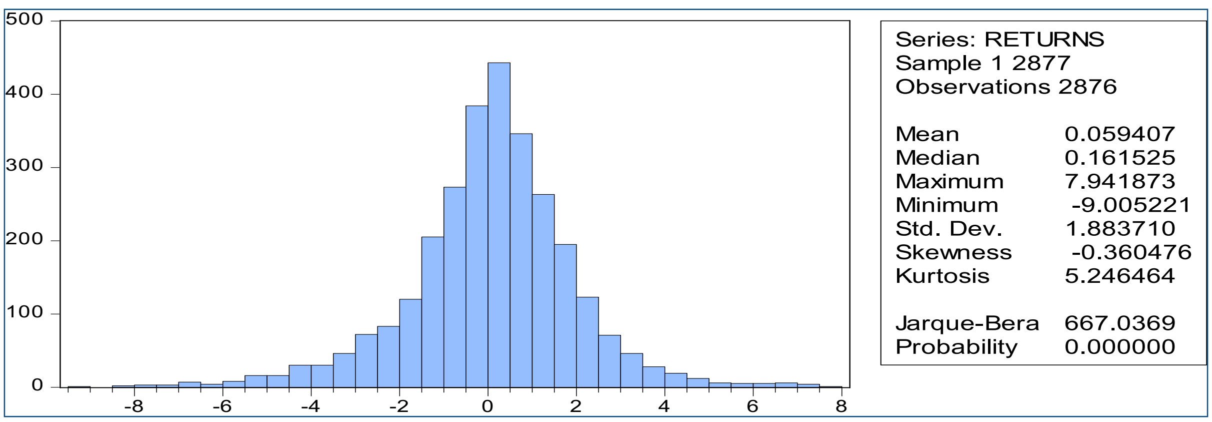


Table 12: Descriptive Statistics of Russia



Analysis of Results

Analysis Table 3 through 12

The log returns of the indices are not normally distributed as the skewness is not equal to zero and kurtosis is more than 3. If the kurtosis is greater than 3, it suggests leptokurtic pattern (slim or long tailed) of the indices. As the skewness in most of the indices are less than zero or negative, it suggests the indices are skewed towards the left. The Jarque Bera Test statistics follows Chi Square distribution, with two degrees of freedom, and the null hypotheses that the log returns of the indices are normally distributed can be rejected, as the p values are also significant.

Table 13 represents unit root calculations and suggests that the calculated values of ADF test statistics for all the indices under the consideration are more than the table value at 1%, 5% and 10% level of significance thus indicate that the continuously compounded returns of all the stock markets are stationary.

Table 13: Unit Root/ Test of Stationarity

	India	*Brazil*	*Srilanka*	*HongKong*	*Indonesia*
Unit Root Test (ADF Test)	-50.87	-53.09	-43.77	-52.75	-47.76
1 5% 10% Critical Value Probability Values	-3.959402 -3.410473 -3.127001 0.000	-3.959591 -3.410565 -3.127055 0.000	-3.960327 -3.410926 -3.127269 0.000	-3.959373 -3.410458 -3.126992 0.000	-3.960318 -3.410921 -3.127267 0.000
	Pakistan	Mexico	South Korea	China	Russia
Unit Root Test (ADF Test)	-46.42	-49.93	-53.82	-52.74	-48.60
1% 5% 10% Critical values Probability Values	-3.960006 -3.410768 -3.127176 0.000	-3.959830 -3.410682 -3.127125 0.000	-3.959119 -3.410334 -3.126918 0.000	-3.959694 -3.410615 -3.127085 0.000	-3.959402 -3.410473 -3.127001 0.000

Test of Volatility

Figs.1 through 10 suggest the volatility graphs of the indices considered for this study and represented in the form of continuously compounded return over a period of ten year. Volatility graphs suggest outliers for all indices particularly during the period of global economic crisis witnessed mostly in 2008. Return series of some indices

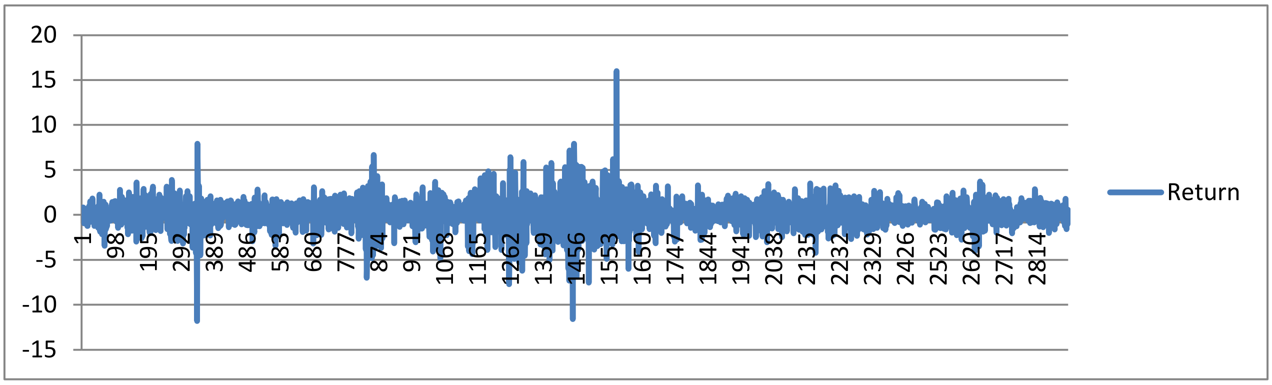


Fig. 1: SENSEX Return Data-India

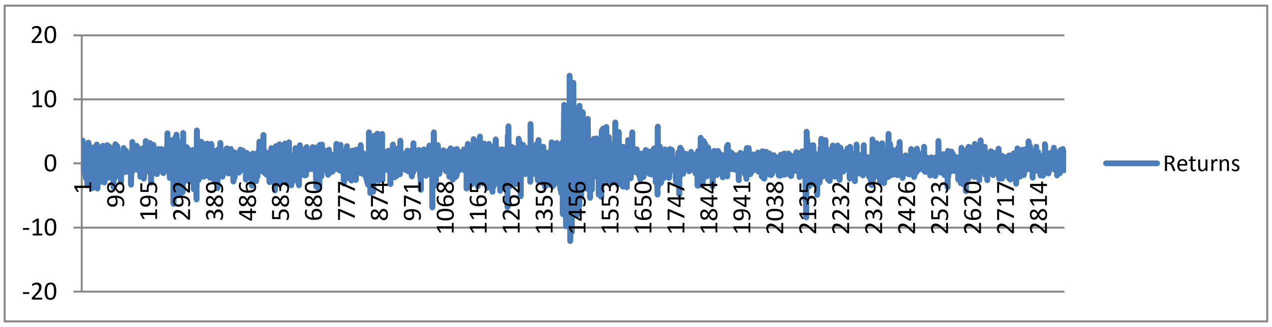


Fig. 2: IBOVESPA Return Data-Brazil

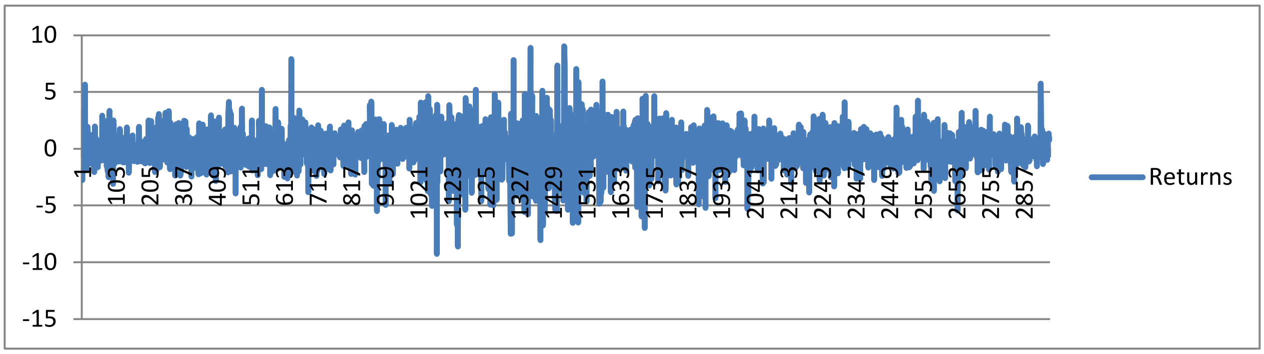


Fig. 3: SSEI Return Data- China

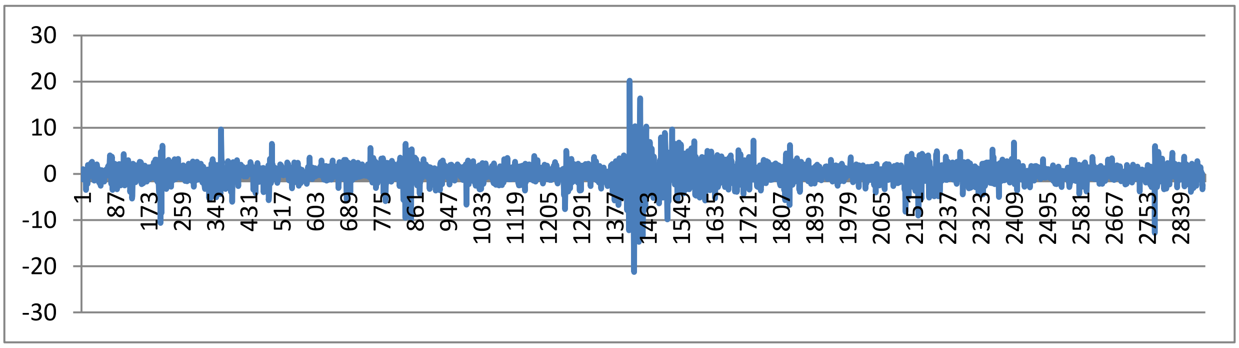


Fig. 4: RTSI Return Data-Russia

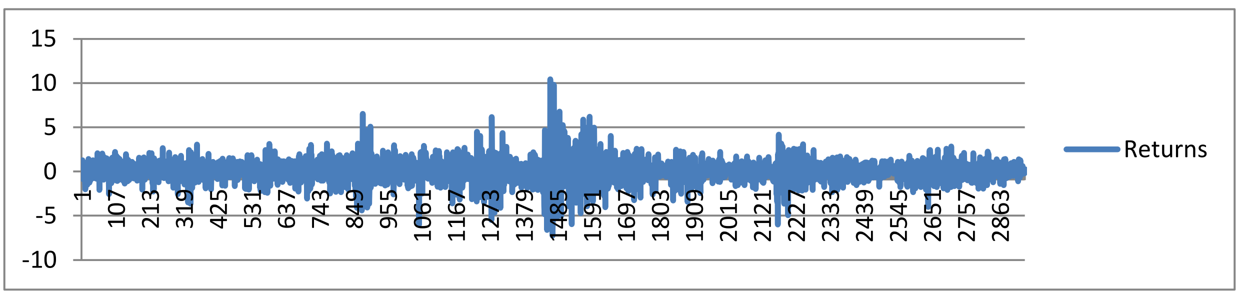


Fig. 5: IPC Return Data- Mexico

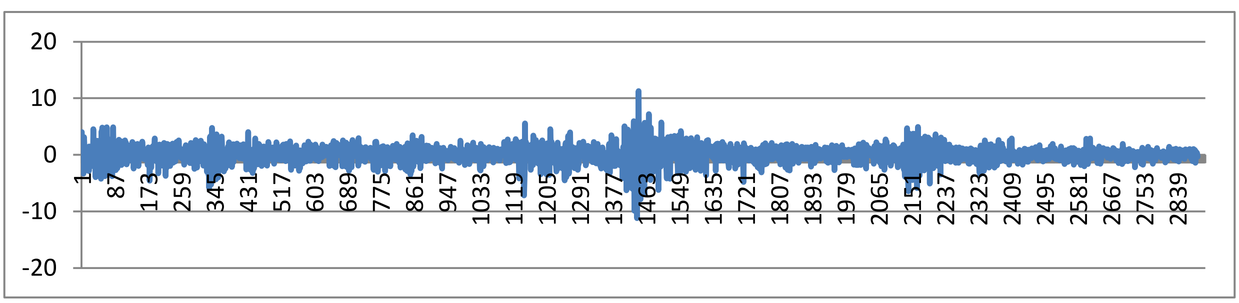


Fig. 6: KOSPI Return Data-South Korea

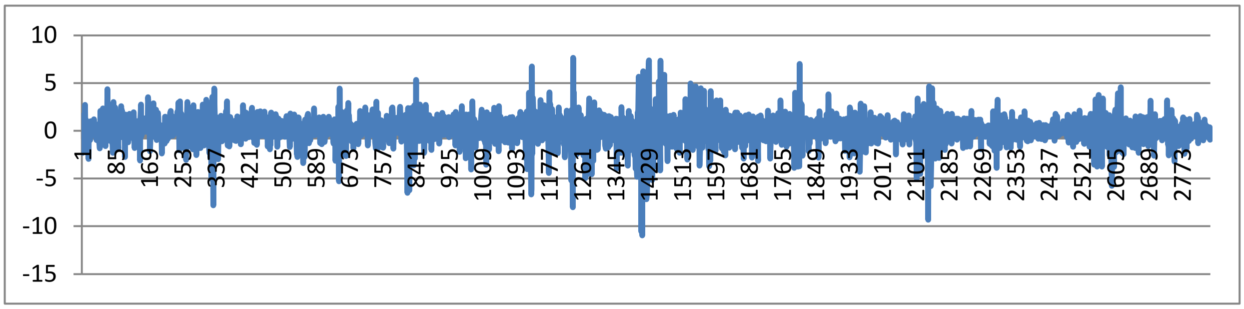


Fig. 7: **JSKE Return Data- Indonesia**

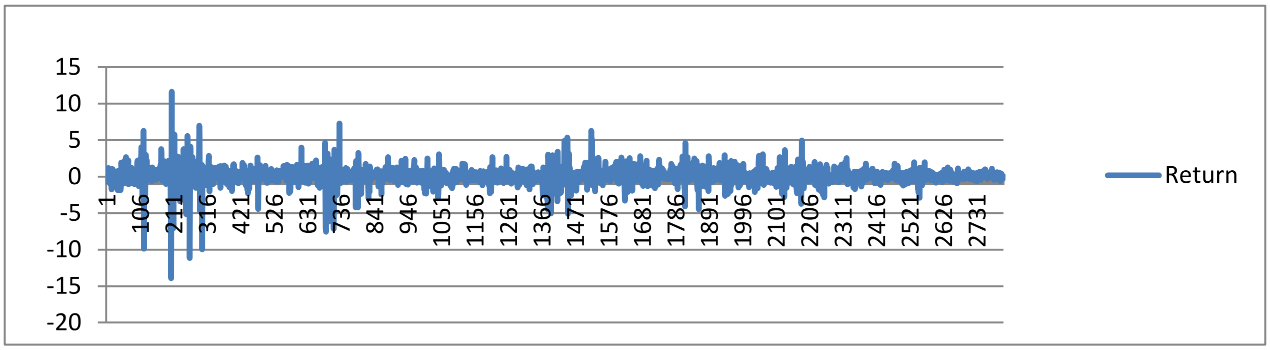


Fig. 8: **ASPI Return Data- Srilanka**

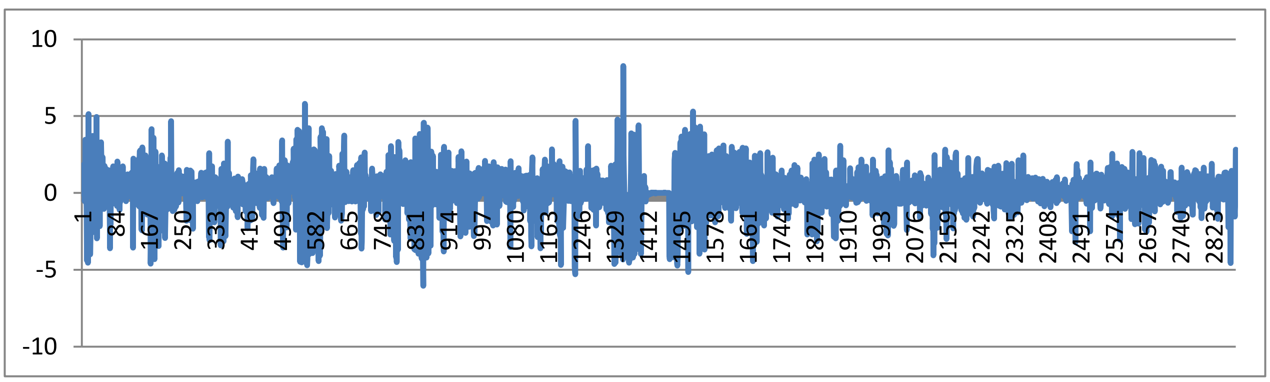


Fig. 9: **KSE 100 Return Data-Karachi Pakistan**

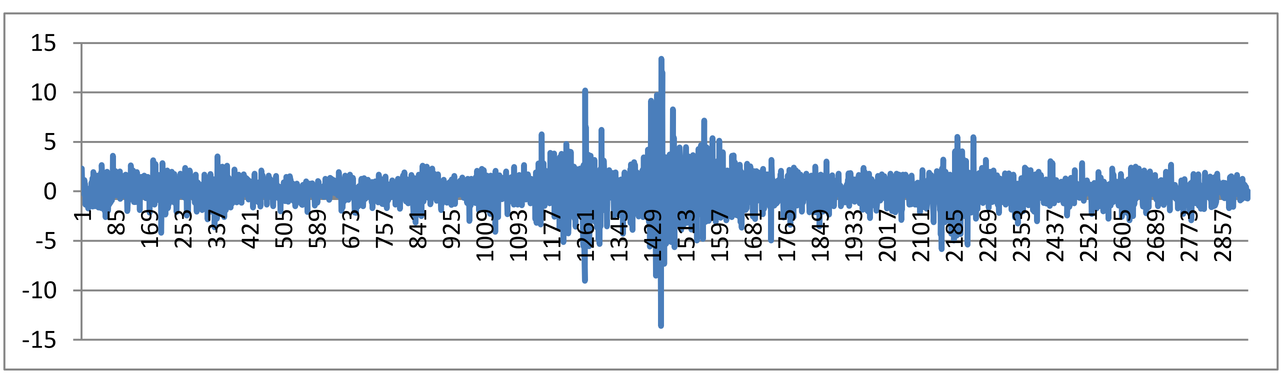


Fig. 10: **HSI Return Data- Hong Kong**

Table 14: Volatility by the measure Standard Deviation

Volatility (%)	*India*	*Brazil*	*Sri-lanka*	*Hong Kong*	*Indo-nesia*	*Pakistan*	*Mexico*	*South Korea*	*China*	*Russia*
Standard Deviation	15	16	11	13.87	14	13.49	13.49	13.74	16	18.83

also occurred to be zero during some periods which are subsequently removed to filter the data along with the outliers for estimating volatility. Volatility graphs also suggest a huge volatility during the year of economic crisis for all indices undertaken for this study. Certain amount of volatility also visible for India during the initial period under the study (2003-04) and a strong volatility is seen during the 19^{th} of May 2009 because of declaration of election results at Centre. For Srilanka, volatility is also visible during the year 2003-04 and Indonesia return data found to be more spiked over the period of study. Hong Kong return data are found to be cluster over the period of study except for the period of economic crisis. SSEI, China return data also suggest more volatility in the form spiked.

Table 13 suggests that calculated volatilities by the measure of standard deviation in the BRIC countries are relatively higher than the other emerging economics and hence it can be interpreted that BRIC stock exchanges are happened to be more volatile during the period of study in comparison to other emerging economics.

Table14 represents appropriate ARMA models, fitted by employing BOX-Jenkins methodology, for all the indices under the study. Fitted ARMA models mostly follow moving average pattern except for Srilanka, Hong Kong and Pakistan where Autogressive pattern is found with the moving average pattern, however for Hong Kong return series suggest a pure AR pattern. Longer moving average patterns in the return series suggest persistent shocks in the system over a period of time.

Table 15: Fitted Autoregressive Moving Average (ARMA) Model

Model	*India*	*Brazil*	*Sri-lanka*	*Hong Kong*	*Indo-nesia*	*Pakistan*	*Mexico*	*South Korea*	*China*	*Russia*
ARMA	MA(1) MA(11) MA(17)	MA(2)	AR(1) MA(4) MA(8) MA(10) MA(11)	AR(2)	MA(1)	AR(1) MA(3) MA(4) MA(9)	MA(1) MA(6)	MA(4) MA(8) MA(14) MA(15)	MA(3) MA(4) MA(6) MA(15)	MA(1) MA(5) MA(13)

Table 16: Volatility Estimation Employing GARCH and EGARCH

India	*Model*		*Model*	
	GARCH		EGARCH	
	α_0	0.033379	α_0	-0.13562
	α_1	0.094767	α_1	0.193995
	β_1	0.88976	γ_1	-0.07542
	$\alpha_0+\alpha_1+\beta_1$	1.00	β_1	0.972056
Brazil	GARCH			
	α_0	0.040611	α_0	-0.06469
	α_1	0.049916	α_1	0.112963
	β_1	0.933752	γ_1	-0.06916
	$\alpha_0+\alpha_1+\beta_1$	1.00	β_1	0.974143
China	GARCH			
	α_0	0.025262	α_0	-0.07454
	α_1	0.045459	α_1	0.111993
	β_1	0.943775	γ_1	-0.01344

India	*Model*		*Model*	
	$\alpha_0+\alpha_1+\beta_1$	1.00	β_1	0.988667
Russia	GARCH			
	α_0	0.098524	α_0	-0.07701
	α_1	0.083721	α_1	0.161196
	β_1	0.88692	γ_1	-0.04974
	$\alpha_0+\alpha_1+\beta_1$	1.00	β_1	0.960792
South Korea	GARCH			
	α_0	0.014052	α_0	-0.10871
	α_1	0.071525	α_1	0.154035
	β_1	0.920941	γ_1	-0.08875
	$\alpha_0+\alpha_1+\beta_1$	1.00	β_1	0.978327
Mexico	GARCH			
	α_0	0.018446	α_0	-0.10546
	α_1	0.078074	α_1	0.147604
	β_1	0.910024	γ_1	-0.09249
	$\alpha_0+\alpha_1+\beta_1$	1.00	β_1	0.97836
Hong Kong	GARCH			
	α_0	0.00957	α_0	-0.07874
	α_1	0.048915	α_1	0.110451
	β_1	0.945203	γ_1	-0.04709
	$\alpha_0+\alpha_1+\beta_1$	1.00	β_1	0.986849
Srilanka	GARCH			
	α_0	0.051742	α_0	-0.33506
	α_1	0.265401	α_1	0.444684
	β_1	0.721274	γ_1	-0.04339
	$\alpha_0+\alpha_1+\beta_1$	1.00	β_1	0.932752
Indonesia	GARCH			
	α_0	0.060962	α_0	-0.14987
	α_1	0.125276	α_1	0.233294
	β_1	0.845768	γ_1	-0.08485
	$\alpha_0+\alpha_1+\beta_1$	1.00	β_1	0.953201
Pakistan	GARCH			
	α_0	0.077503	α_0	-0.16405
	α_1	0.138171	α_1	0.280939
	β_1	0.81608	γ_1	-0.12462
	$\alpha_0+\alpha_1+\beta_1$	1.00	β_1	0.895392

Table 15 represents the estimated volatility by employing GARCH(1,1) and EGARCH(1,1) for all the emerging markets considered for this study. The table suggests that the coefficients α_0, α_1, β_1 and $\boldsymbol{\gamma_1}$ are statistically significant and are within parametric restriction for all the period under the study, thus implying a greater impact of shocks (or news) on volatility. A significant ARCH coefficient α_1 indicates a large shocks on day t_{-1} leads to large (conditional) variance on day t. α is the "news" component that explains that recent news has a greater impact on price changes and it implies the impact of yesterday's news on today's volatility.The GARCH coefficient β_1 measures the impact of "old news". In this study EGARCH model is used to capture the tendency for negative shocks to be associated with increased volatility. The logarithm form of the conditional variance implies that the leverage effect is exponential (so the variance is non-negative) is also shown in the table. The presence of leverage effects can be tested by the hypothesis that $\gamma < 0$ and if $\gamma \neq 0$, then the impact is asymmetric. α_1 for Srilanka, Indonesia and Pakistan are found to be the highest in comparison to other markets. β_1 for most of the countries is found to be high except for Srilanka. Presence of asymmetry in volatility of the indices during the periods suggest that the volatility is more in the markets whenever negative information flows into the market in comparison to the positive news. Pakistan has the highest value of $\boldsymbol{\gamma_1}$ which suggest more impact of market volatility because of negative information.

Conclusion

Volatility estimations across the countries are found to be high during the period of global economic crisis. Asymmetric information found to be impacted all the countries during the period of study and volatility in Pakistan, Srilanka, and Indonesia are mostly impacted through recent information.

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