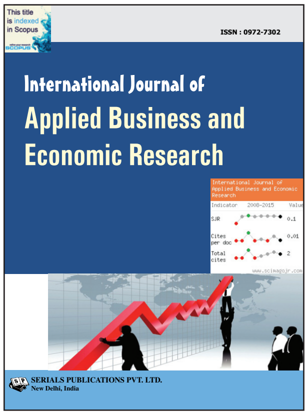

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Modelling of Volatility and Stylized Facts of Emerging Stock Market: Evidence from India

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ABSTRACT

This paper empirically estimates the volatility of stock returns in National Stock Exchange of India (NSE) and Bombay Stock Exchange (BSE) by using symmetric and asymmetric GARCH models. Daily data of Nifty 50, Nifty midcap 100, BSE 30 Sensex and BSE 200 index covering the period from 30th September, 2006 to 15th, September, 2016 were used for analysis.

Lagrange Multiplier (LM) test was employed to check the presence of heteroscedasticity in residual of returns series. LM test reveals the presence of ARCH effects in returns of Nifty 50, Nifty midcap 100, BSE 30 Sensex and BSE 200 indices.

The result from GARCH model reveals that previous and current news had impacts on conditional volatility of stock returns in NSE and BSE. The result from TGARCH and EGARCH models suggest that bad news generates more conditional volatility than good news of same magnitude. The result of Power GARCH models however show that positive shocks increases conditional volatility than negative shocks of same magnitude. Finally the result shows that the existence of persistence volatility, asymmetric effects and volatility clustering in National Stock Exchange of India (NSE) and Bombay Stock Exchange of India (BSE).

JEL: G02, G17

Keywords: Volatility, Stylized facts and GARCH modelling.

1. INTRODUCTION

Estimation of volatility of financial markets is extremely important in recent financial literature because it has wide implications for investors, option pricing strategies and managing risk. Many studies have argued that volatility of equity markets in world are estimated through symmetric and asymmetric GARCH models. Further equity markets basically characterized by fat tails, volatility clustering, mean reversion, persistence volatility and leverage effects among others. The GARCH and related estimation of techniques are mainly developed to capture these characteristics that are generally linked with financial markets.

There are few studies that estimate the volatility and stylized facts of emerging stock markets like India using GARCH model. For example Karmakar (2005) used a GARCH related techniques to estimate the volatility in Indian stock market and found an existence of asymmetric effect and clustering volatility in Indian stock market. Goudarz (2010) also employed GARCH estimation techniques to estimate the volatility in National Stock Exchange of India (NSE). The result revealed existence of volatility persistence and mean reversion behavior in NSE. Mishra and Rahman (2010) found that negative shocks tend to have more conditional volatility than positive shocks. The study also shows presence of asymmetric effect in Indian stock market. Rakesh Kumar (2013) employed GARCH models to examine the nature of volatility of stock market in India. The results revealed that an existence of leverage effect and high level of persistence of shocks in volatility of Indian stock market. Therefore, it is important to investigate the nature of volatility and stylized facts of Indian stock market. Understanding the nature of volatility is extremely important to investors could able to hedge or speculate against movement of stock prices.

2. EMPIRICAL EVIDENCE

Ahmed and Suilman (2011) examined the nature of volatility in Khartoum Stock Exchange (KSE) by employing GARCH models. For analysis daily data was taken from 2nd January 2006 to 30th November, 2010. The result shows that there was high persistence volatility in returns of Khartoum Stock Exchange (KSE). The result futher reveals the existence of leverage effects in KSE. Adesina (2013) employs symmetric and asymmetric GARCH models to estimate volatility of stock returns in Nigerian Stock Exchange (NSE). Monthly data of all share indices for the period from January 1985 to December 2011 was used for the analysis. The study revealed that previous news had greater impacts on current volatility and there was also existence of persistent volatility in stock returns of NSE. Finally the result reveals that asymmetric effect was absent in returns of all share indices. Goudarzi and Ramanarayanan (2011) employed EGARCH and TGARCH models to examine presence of symmetric volatility in Bombay Stock Exchange (BSE). Daily data from BSE 500 index spanning from 26th July 2000 to 20th January 2009 was used for the analysis. The findings from the study indicated the presence of leverage effect in BSE.

Karmakar (2005) examined the nature of volatility of stock returns in NSE and BSE. Using daily data from Nifty 50 and BSE 30 Sensex for the period 2nd January, 1991 to 10thJune, 2003, GARCH related estimation techniques were applied to the data set. Daily data on 50 individual stocks were also used to measure volatility of these stocks. The result reveals presence of leverage effect, time varying volatility and volatility clustering in Indian Stock market. Tripathy and Gil-Alana (2015) examined the nature of volatility of stock returns in Indian stock market. The study employs GARCH related estimation techniques to capture the presence volatility clustering and asymmetric behavior in daily data of Nifty 50 covering period from 3rdAugust 1992 to 21st September 2012. The result shows the presence of leverage effect in the Nifty index.

Karanasos et. al., (2013) employed univariate and multivariate GARCH estimation techniques to examine time varying volatility o International stock markets. Daily data of FTSE, DAX and Nikkei 225 from 1st January 1988 to 30th, June 2010 were used for the analysis. The result revealed the presence of asymmetric effect and time varying volatility across international stock markets. Finally the result shows that volatility spillover was found across international stock markets. Alberga et. al., (2008) estimate volatility of stock returnsin Tel Aviv Stock Exchange (TASE) by employing GJR GARCH and PGARCH models. For analysis, daily data of TA25 from 20th, October 1992 to 31st, May 200 was taken from yahoo finance. The result reveals that bad news increases conditional variance than good news of same magnitude. There was evidence of leverage effect in TASE.

From forgoing empirical studies on the modelling of volatility of stock returns is reviewed, it is observed that mixed results both in India and outside of India has been found. Therefore present study re-investigates the nature of volatility of stock returns in BSE and NSE.

3. DATA AND METHODOLOGY

Data Description

Data for the present study was obtained from official website of Bombay Stock Exchange of India (BSE) and National Stock Exchange of India (NSE). Daily data of Nifty 50, Midcap 100, BSE 200 index and BSE 30 sensex covering the periods from 30th September, 2006 to 15th, September, 2016 were collected to estimate the volatility of these indices. All closing series were converted to natural logarithm to check stationarity. Daily returns were calculated using the equation $R_t = \log (P_t/P_{t-1}) \times 100$ where, R_t is the daily returns, P_t is the value of the stocks at time t, P_{t-1} is the previous value of the stocks.

Methodology

Firstly the Augmented Dickey- Fuller (ADF) and Phillips–Perron tests proposed by Dickey and Fuller (1976) and Phillips and Perron (1988) respectively were conducted to ascertain the stationarity properties of the series used in the study. Secondly, symmetric and asymmetric GARCH models were used to estimate the volatility of stock market in India. Stock market was basically characterized by fat tails, volatility clustering, mean reversion, persistence volatility and leverage effects. The GARCH related estimation techniques are mainly developed to capture these characteristics that were generally linked to stock market. In GARCH model, the conditional variance depends upon squared *past* the error terms and conditional variances. GARCH model suggested by Bollerslev (1986) is specified as follows:

$$h_t = \alpha_0 + \alpha_1\varepsilon^2_{t-1} + \alpha_2\varepsilon^2_{t-2} + ... + \alpha_q\varepsilon^2_{t-q} + \beta_1 h_{t-1} + \beta_2 h_{t-2} + ... + \beta_p h_{t-p}$$

$$h_t = \alpha_0 + \sum_{i=1}^{q}\alpha_1\varepsilon^2_{t-1} + \sum_{j=1}^{p}\beta_j h_{t-j}$$

where, $p \geq 0, q \geq 0$

$\alpha_0 > 0,\ a_1 \geq 0,\ i = 1, 2, \ldots, q$

$\beta_1 \geq 0,\ i = 1, 2, \ldots, p.$

Threshold GARCH (TGARCH 1, 1)

One of the stylized facts of stock market was asymmetric behavior. It implies that bad news increases conditional volatility than goodnews. Therefore, TGARCH is applied to capture asymmetric effect tin Indian stock market. The threshold GARCH model was developed by Zakoian (1990) and Gltosan, Jagannathan and Runkle, (1993). This model mainly explain how negative and positive shocks impacts conditional volatility. TGARCH (1, 1) model the specification is as follows.

$$h_t = \alpha_0 + \sum_{j=i}^{q} \alpha_1 \varepsilon_{t-1}^2 + \sum_{i=1}^{p} \beta_1 h_{t-1} + \sum_{k=1}^{r} \gamma_i d_{t-1} \varepsilon_{t-1}^2$$

where, $d_{t-1} = 1$ if $\varepsilon_{t-1} < 0$, $d_{-1} = 0$ if other wise

Exponential GARCH (EGARCH 1 1)

Exponential GARCH (EGARCH) proposed by Nelson (1991) captures the asymmetric effect which was present in time series data. The specification of EGARCH (1,1) model is as follows.

$$\log(h_t) = \delta_0 + \sum_{j=1}^{q} \theta_j \log(h_{t-j}) + \sum_{i=1}^{p} \lambda_i \left| \frac{u_{t=i}}{\sqrt{h_{t=i}}} \right| + \sum_{k=1}^{r} \gamma_k \frac{u_{t-k}}{\sqrt{h_{t-k}}}$$

Leverage effect exists if $\gamma_k = 0$ and impact is asymmetric if $\gamma_k \neq 0$. It indicates bad news tend to have more volatility than good news. Finally the power GARCH was used to explore asymmetry volatility in Nifty 50, Nifty Midcap 100, BSE 30 sensex and BSE 200 index.

4. EMPIRICAL RESULTS AND DISCUSSION

The results obtained from Dickey-Fuller and Phillips – Perron tests are reported in Table 1. The result reveals that the log series of Nifty 50 index, Nifty Midcap 100, BSE 30 Sensex and BSE 200 were non-stationary at levels.

Table 1
Unit root Test Statistics

Index	*ADF Test*		*P-P Test*	
	Level	*First Difference*	*Level*	*First Difference*
Nifty index 50	–1.3321	–23.450*	–1.3890	–23.567*
Nifty Midcap 100	–0.4219	–26.891*	–0.3901	–26.991*
BSE 30 Sensex	–1.2890	–34.724*	–1.3190	–34.934*
BSE 200 Index	–1.1890	–25.890*	–1.2890	–25.543*

Notes: *indicates 1 percent level of significance

However all log series become stationary after first differencing since null hypothesis was rejected at 1 per cent significance level. The log series of Nifty 50, Nifty Midcap 100, BSE 30 Sensex and BSE 200 Index are further shown in Figure 1 to 4 respectively.

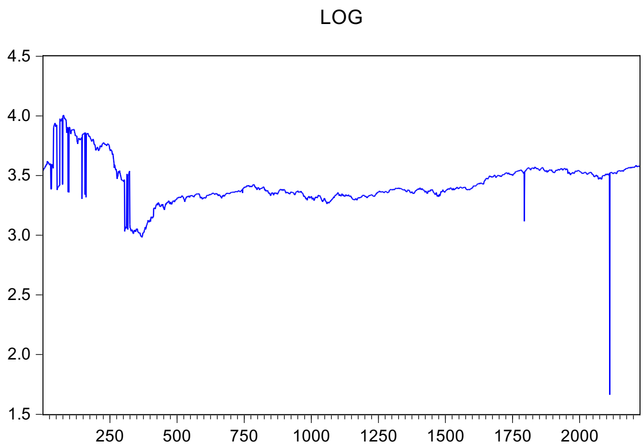

Figure 1: Log Series of BSE 200

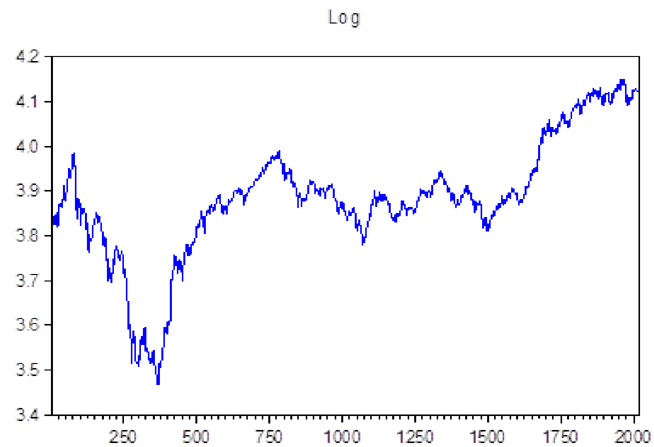

Figure 2: Log Series of Nifty Mid 100

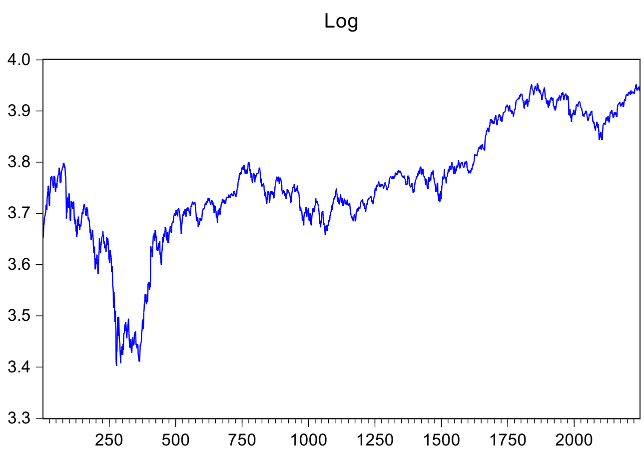

Figure 3: Log Series of Nifty 50

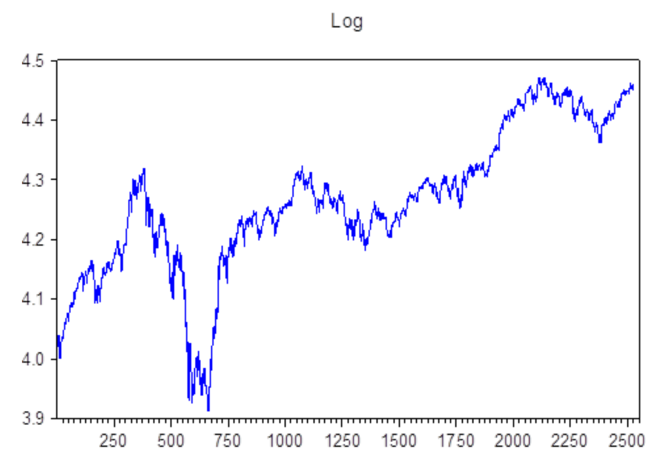

Figure 4: Log Series of BSE 30 Sensex

The descriptive statistics is reported in Table 2. The mean returns of all indices were positive except Nifty Midcap 100. The standard deviation of Nifty 50 and BSE 30 Sensex were high among the series. It indicates that higher volatility in Nifty 50 and BSE 30 Sensex as compared to other indices. The negative coefficients of skew-ness imply that the frequency distribution of the return series was negatively skewed or has longer tails to left. The kurtosis value exceeds three for most of the indices which shows that the distribution of returns had fatter tails over sampled period. The Jarque–Bera test statistics show that returns on Nifty 50, Nifty Midcap 100, BSE 30 sensex and BSE 200 index follow non normal distribution since null hypothesis of normal distribution was rejected.

Table 2
Descriptive Statistics

Name of Index	*Mean*	*S-D*	*Skewness*	*Kurtosis*	*J.B Test*	*LM Test*	*LB Q(16)*
BSE 30 Sensex	0.00471	0.34267	–0.6329	9.5430	243.22	44.382	23.901
BSE 200 Index	0.00891	0.00712	–0.8342	18.901	3451.90	28.280	45.901
Nifty Midcap 100	–0.00271	0.00271	–0.9921	56.891	287.90	786.34	78.119
Nifty 50	0.0128	0.2432	–0.7320	13.906	4532.01	19.971	12.932

The Ljung–Box *Q* [LB *Q* (16)] statistics shows that all series are statistically significant, implying returns series auto correlated each other and are linear dependent. The LB *Q* (16) statistics reveals the presence of serial correlation in squared errors. Lagrange Multiplier (LM) test was employed to check the presence of *heteroscedasticity* in residual returns series. LM test reveals the existence of ARCH effects in returns of Nifty 50, Nifty Midcap 100, BSE 30 Sensex and BSE 200 index.

Estimation of GARCH (1, 1)

To examine the nature of volatility of stock returns in National Stock Exchange of India (NSE) and Bombay stock Exchange (BSE) both symmetric and asymmetric GARCH techniques were employed. The results of GARCH model is reported in Table 3.

Table 3
Estimation of GARCH (1,1) Model results

Parameters	*Nifty index 50*	*Nifty Midcap 100*	*BSE 30 Sensex*	*BSE 200 Index*
Constant	0.2351 (2.1180)	0.07821 (1.8390)	0.00032 (1.7115)	0.00342 (1.5743)
ARCH Effect (α_1)	0.37629* (4.2189)	0.42390* (3.2387)	0.31890* (2.6795)	0.48210* (5.7118)
GARCH effect (β_1)	0.64001* (9.1145)	0.58450* (10.7341)	0.69781* (7.8760)	0.58716* (13.675)
($\alpha + \beta$)	1.16	1.11	1.15	1.06
ARCH LM test up to 12 lags				
F Test	1.89760	2.0862	1.7652	1.3210
Probability	0.56230	0.4478	0.3321	0.6897

Notes: *Indicates 1 percent level of significance

The result reveals that coefficient of ARCH was positive and significant implying that previous news had an impact on current volatility of Nifty 50 and BSE 30 Sensex. The GARCH coefficient was also positive and significant indicating that recent news impact on current volatility of stock returns in India. The sum of ARCH and GARCH coefficients 1.16 for Nifty 50 represents the persistent of variance in stock returns. The value indicates that there was a highly persistence in volatility of returns in NSE.

Estimation of TGARCH Model (1, 1)

To investigate the presence of leverage effect in Indian stock market, threshold GARCH (TGARCH) model was employed. The result of TGARCH model is reported in Table 4. The result reveals positive and significant coefficient of asymmetry for Nifty 50 index, BSE 30 Sensex and BSE 200 index. This further implies the existence of asymmetric effect in National Stock exchange of India (NSE) and Bombay Stock Exchange (BSE). This implies that negative shocks had lager effects on conditional variance than positive shocks of same magnitude. However, the coefficient of asymmetry was negative for Midcap 100 which shows absence of asymmetric effect.

Table 4
Estimation of TGARCH (1,1) Model results

Parameters	*Nifty index 50*	*Nifty Midcap 100*	*BSE 30 Sensex*	*BSE 200 Index*
Constant	0.0E562	0.0E1780	0.0E209	0.007840
	(1.7590)	(1.5901)	(1.6202)	(1.8970)
ARCH Effect (α_1)	0.65410	0.53711*	0.4855*	0.7690*
	(4.0978)	(2.8928)	(3.3412)	(5.8912)
GARCH effect (β_1)	0.48390*	0.49319*	0.5991*	0.39031*
	(7.4530)	(9.9012)	(10.1691)	(4.009)
Leverage effect (Υ)	0.004510*	–0.3219*	0.006907*	0.00453*
	(2.8761)	(–3.8538)	(2.9926)	(2.7240)
($\alpha + \beta$)	1.13	1.02	1.07	1.18
ARCH LM test up to 12 lags				
F Test	1.62101	1.99262	2.0076	1.5890
Probability	0.4890	0.5290	0.3290	0.4890

Notes: *indicates 1 percent level of significance

The value of the LM test statistic indicates the absence of additional ARCH effect since null hypothesis was not rejected.

Estimation of EGARCH model (1, 1)

The exponential GARCH (EGARCH) model was applied to test for the existence of asymmetric effects on returns of Nifty 50 Index, Nifty Midcap 100, BSE 30 Sensex and BSE 200 Index**.** The results are reported in Table 5.

Table 5
Estimation of EGARCH model (1, 1) results

	Nifty index 50	*Nifty Midcap 100*	*BSE 30 Sensex*	*BSE 200 Index*
Constant	0.0E3891	0.002318	0.0E5641	0.007840
	(1.3780)	(1.4726)	(1.4509)	(1.8970)
ARCH Effect (δ)	0.3781*	0.37012*	0.5641*	0.7690*
	(2.8901)	(3.7890)	(4.8964)	(5.8912)
GARCH effect (λ)	0.78893*	0.79638*	0.51970*	0.39031*
	(5.7821)	(8.6704)	(14.896)	(4.009)
Leverage effect (Υ)	–0.03418*	–0.4481*	–0.06543*	–0.008631*
	(–2.5790)	(–2.781)	–(1.9932)	(–2.1892)
($\alpha + \beta$)	1.15	1.16	1.07	1.15
ARCH LM test up to 12 lags				
F Test	1.9231	1.7216	2.1562	1.6380
Probability	0.6711	0.3826	0.4219	0.3389

Notes: *indicates 1 percent level of significance

The result reveals that coefficient of ARCH and GARCH were positively significant implying that previous and current news had impacts on conditional variance. The asymmetric effect captured by the leverage effect (ϒ) was negatively significant which shows that bad news (negative shocks) had greater impacts on conditional variance than good news (positive shocks) of same magnitude. This result further reveals the existence of asymmetric effect in National Stock Exchange of India (NSE) and Bombay Stock Exchange (BSE). The ARCH-LM statistics shows absence of additional heteroscedasticity in residuals of return series.

Estimation of Power GARCH model (1, 1)

This paper empirically investigates the presence of asymmetric effects in National Stock Exchange of India (NSE) and Bombay Stock Exchange (BSE) by using power GARCH model. The results of power GARCH model are reported in Table 6.

Table 6
Estimation of Power GARCH model (1, 1) results

Parameters	*Nifty index 50*	*Nifty Midcap 100*	*BSE 30 Sensex*	*BSE 200 Index*
Constant	0.00034	0.0E301	0.0E209	0.00329
	(1.2671)	(1.4710)	(1.6202)	(1.6432)
ARCH Effect (α_1)	0.8231*	0.6810*	0.4855*	0.4439*
	(6.9821)	(5.8910)	(3.3412)	(6.0087)
GARCH effect (β_1)	0.39810*	0.49012*	0.6991*	0.78021*
	(3.7790)	(12.3401)	(10.1691)	(4.009)
Leverage effect (ϒ)	0.00781*	0.00231*	0.32898*	0.0891*
	(2.6712)	(3.9010)	(1.9932)	(2.9920)
($\alpha + \beta$)	(1.21	1.02)	1.17	1.14
ARCH LM test up to 12 lags				
F Test	2.0071	1.9932	1.8832	1.3419
Probability	0.3180	0.4510	0.5610	0.4480

Notes: *indicates 1 percent level of significance

The result in Table 6 shows that coefficients of ARCH and GARCH were positively significant. The asymmetric coefficient was also positively significant which shows that positive shocks increases conditional volatility than negative shocks of same magnitude. The result also indicates the presence leverage effect in returns of Nifty 50, Nifty Midcap 100, BSE 30 Sensex and BSE 200 index. The LM statistics indicates the absence of additional ARCH effect in all returns series and variance equation specified.

5. SUMMARY AND CONCLUDING REMARKS

Estimation of volatility of stock returns is important in recent financial literature because of its wider implications for investors, option pricing strategies and risk management. This paper empirically estimates volatility of stock returns in National Stock Exchange of India (NSE) and Bombay Stock Exchange (BSE) using symmetric and asymmetric GARCH models. Daily data of Nifty 50, Nifty midcap 100, BSE 30 Sensex and BSE 200 index were collected from 30th September, 2006 to 15th September, 2016 for the analysis. Lagrange Multiplier (LM) test was employed to check the presence of *heteroscedasticity* in residuals of returns series. LM test reveals the presence of ARCH effects in returns of Nifty 50, Nifty midcap 100, BSE 30 Sensex and BSE 200 index.

The GARCH result shows that previous and current news had impacts on conditional volatility of stock returns in NSE and BSE. The result of TGARCH and EGARCH indicate that bad news increase conditional volatility than good news of same magnitude. Finally the result shows that the there was an existence of persistence volatility, asymmetric effect and volatility clustering in National Stock Exchange of India (NSE) and Bombay Stock Exchange of India (BSE).

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