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ORIGINAL PAPER

Modeling emerging stock market volatility using asymmetric GARCH family models: An empirical case study for BSE Ltd. (formerly known as Bombay Stock Exchange) of India

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Abstract:
This study focuses on volatility estimation using asymmetric GARCH family models in financial series of S&P BSE LargeCap index collected from BSE Limited (formerly known as Bombay Stock Exchange) of India. The objective of this paper is to investigate volatility in market, asymmetry in volatility, measure short and long term volatility persistence and impact of news on market. This study considers data from 01:2005 to 05:2020 counting 3818 daily observations and follows GARCH (1, 1), EGARCH (1, 1) and GJR (1, 1). The empirical results indicate the following:1) presence of changing asymmetry in series returns of S&P BSE LargeCap index and evidence of leverage effect, 2) presence of abnormal volatility shocks which indicates high investment risk, 3) estimated impact of news and effect on market and 4) an opportunity for investment and return prospects. Main results and findings include all data statistics outcomes with graphical explanations. Furthermore, detailed result statistics available in full for GARCH and GARCH family models.

Keywords: *Financial econometrics; GARCH family models; Financial markets; Stock market; Volatility.*
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1. Introduction

The main objective of this research paper is to provide complex framework on emerging stock market volatility using asymmetric GARCH family models based on an empirical case study of Bombay Stock Exchange of India. Stock market represents a volatile behavior. Before daily closing of any stock market, several times index moves up and down. It is believed that emerging stock market has higher volatility compare to developed stock market. This paper focuses on one of the segment of Bombay Stock Exchange, namely BSE500. In recent past, there are several incidents for great fall down in global stock markets even after global financial crisis, with one or other particular reasons. More interestingly stock market can be divided into two parts; (i) predictable market and (ii) unpredictable market. Predictable market delineates absolute possibility of super risks and great losses, whereas unpredictable market shows possibility of returns. Volatility creates degree of risk factor and can be read two sides; (i) possibility for higher losses (ii) possibility for higher returns. Such kind of investigation and prediction requires advance statistical methodology which can provide idea about past moment so that an investor can predict an opportunity for return on investment. There are several methods but among the most used is ARCH by Engle (1982) and GARCH model designed by Bollerslev (1986). Such statistical analysis considers volatility as conditional variance. Black (1976) has introduced new facts about stock market volatility, i.e. the leverage effect. It means that the losses have greater influence than do gains. Asymmetry represents the impact of distribution of losses and expected greater tail than do gains.

This study on &P BSE LargeCap index and the aim to find out (i) the volatility (ii) leverage effect and asymmetry (iii) impact of news and (iv) finding out an opportunity for investment in &P BSE LargeCap index. GARCH stands for generalized autoregressive conditional heteroskedasticity and identified as most used econometric tool to analyze time series and stock market.

2. Literature review

In this research paper we follow GARCH (1, 1) by Bollerslev (1986) to model the volatility, and other GARCH based models to test leverage effect and asymmetry, such as EGARCH, Exponential GARCH designed by Nelson (1991) and GJR – GARCH by Glosten, Jagannathan and Runkle (1993). Alberg et al. (2008) worked on a comprehensive empirical analysis focused on the mean return and conditional variance of Tel Aviv Stock Exchange (TASE) indices is performed using various GARCH models. The empirical findings revealed that asymmetric GARCH model based on fat-tailed distributions provides improved estimation results in case of conditional variance, while EGARCH model is the most suitable for prediction of TASE indices. Trivedi et al. (2021) investigated volatility spillovers between certain developed and emerging stock markets in the European Union based on GARCH family models.

Furthermore, Chen and Kuan (2002) investigated the dynamics of US stock market returns by applying GARCH and EGARCH models. However, EGARCH, which is also known as Exponential GARCH designed by Nelson (1991) fits well on most of financial series and captures stylize facts of series returns. The use of the new hybrid asymmetric volatility methods can simultaneously decrease the stochastic and nonlinearity of the error term sequence, while capturing the asymmetric volatility (Tseng et al., 2008). Moreover Marcucci (2005) applied standard GARCH models in order to predict the volatility pattern of US financial market.

Engle and Rangel (2008) suggested that "Volatility is higher for emerging markets and for markets with small numbers of listed companies and market capitalization, but also for large economies". Spulbar et al. (2020) examined volatility spillover effect between emerging and developed stock markets, including the case of India and argued that an international diversification strategy has a considerable influence on guaranteeing the portfolio value based on decreasing aggregate investment risk and stock returns volatility. It is also important to consider international portfolio diversification strategy in order to achieve significant potential benefits. Moreover, Pinto et al. argued that: "stocks with low historical volatility exhibit superior risk-adjusted returns and higher absolute returns over high volatility stocks".

On the other hand, Ejaz et al. (2020) have highlighted that emerging stock markets represent a source of much more attractive portfolio diversification opportunities in comparation with developed stock markets. Spulbar and Birau (2019) pointed out that international linkages which implies causality and interdependence between developed and emerging stock markets determine the effect of dynamic transmission patterns based on the spread of financial shocks. However, Zulfiqar et al. (2020) revealed that: "stock markets which operate under efficient governance and institutional environments experience greater stock returns and lower level of risk." Hemanth and Basavaraj (2016) have conducted an empirical research study on volatility prediction based on GARCH models and concluded that in case that volatility suffers a change at higher rate, the result may consists of either high profits or high losses. However, Nethravathi et al. (2020) indicated that using correlation can effectively contribute to detect the degree to which certain two variables are connected to each other.

Castaño (2010) studied general index of stock exchange of Colombia and its volatility using GARCH type models. The paper follows EGARCH modeling and results suggest that importance of asymmetric modeling and EGARCH which captures stylized facts of financial market of Colombia. This paper's objectives are to explore the volatility, stylize facts of financial series and impact of news on stock market returns of BSE - Large Cap series by using GARCH (1, 1) designed by Bollerslev (1986), exponential GARCH or EGARCH model designed by Nelson (1991) and GJR – GARCH designed by Glosten, Jagannathan and Runkle (1993).

Tripathi and Sethi (2010) argued that the essential pillars that determine the financial integration of stock market include the following: bilateral trade relationships, interest rate differential, inflation differential, but also stock market main features such as size and return volatility. Mukherjee and Mishra (2005) investigated stock market interlinkages and concluded that the stock market from India is characterized by an integration relationship with the following emerging stock markets in Asia, i.e.: Indonesia, Malaysia, Korea, Philippines and Thailand.

Bonga (2019) investigated relevand issues on Stock Market Volatility using GARCH models, such as GARCH(1,1), GARCH-M(1,1), IGARCH(1,1) and EGARCH(1,1) models based on an empirical case study for Zimbabwe Stock Exchange (Africa). The empirical findings revealed that Exponential GARCH (1,1) or E-Garch (1,1) model has proven to be the most suitable model while asymmetric coefficient have been significant.

3. Research methodology

This empirical study consists of 3.818 daily observations of financial series of S&P BSE LargeCap index from the sample period of January 2005 to May 2020, were obtained from official website of Bombay stock exchange. Before process to statistics, we have converted S&P BSE LargeCap index series to log returns and computed first log difference of the series. Data statistics than processed to compute basic statistics and original series return and converted stationary series returns (see table no.1 and figure no.2). The fundamentals of financial market volatility analysis has been completely changed after immediate introduction of asymmetry GARCH models such as GARCH-M, EGARCH, GJR-GARCH, T-GARCH etc. Asymmetry and Leverage effect explores deep stylized facts of BSE500 series returns. Application of such econometric tools can proceed only after white noise process (stationary of data series) and with this paper it has been tested with ADF test by using following formula. The ADF (Augmented Dickey Fuller) test is the augmented version of Dickey Fuller test and used to determine if the variables are stationary. Most of financial time series face autocorrelation problem and thus it can be augmented by adding various lagged dependable variables. The ADF test formula is the following:

$$\Delta y_t = (\rho - 1) y_{t-1} + \alpha_i \sum_{i=1}^{m} \Delta y_{t-i} + u_t$$

In the above formulation the correct value of m represents number of lags. The aim of Augmented Dickey Fuller test is to maximize the amount of information. During the ADF test we confirm the ARCH effect and no unit root problems at level of 10%, 5% and at level of 1%. We consider results at level of 1%. ADF test statistics is computed twice i.e. with constant and trend by considering 4 lag as maximum order and considered 16 lags order.

4. Empirical results and discussion

Augmented Dickey-Fuller test results with constant and trend including 16 lags of (1-L)(max was 4, criterion AIC) sample size 3818 unit-root null hypothesis: a = 1, with constant and trend model: (1-L)y = b0 + b1*t + (a-1)*y(-1) + ... + e where estimated value of (a - 1): -0.637421, test statistic: tau_ct(1) = -11.87 asymptotic p-value 1.624e-024, 1st-order autocorrelation coefficient for e: 0.000, lagged differences: F(16, 3783) = 4.755 [0.0000]. ADF test statistics indicates that the series is stationary and follows no unit root problems. Furthermore, the series returns also processed with ACF and PACF tests autocorrelation function tests provides significance level at 10%, 5% and at level of 1% using standard error 1/T^0.5 (see Figure no.1).

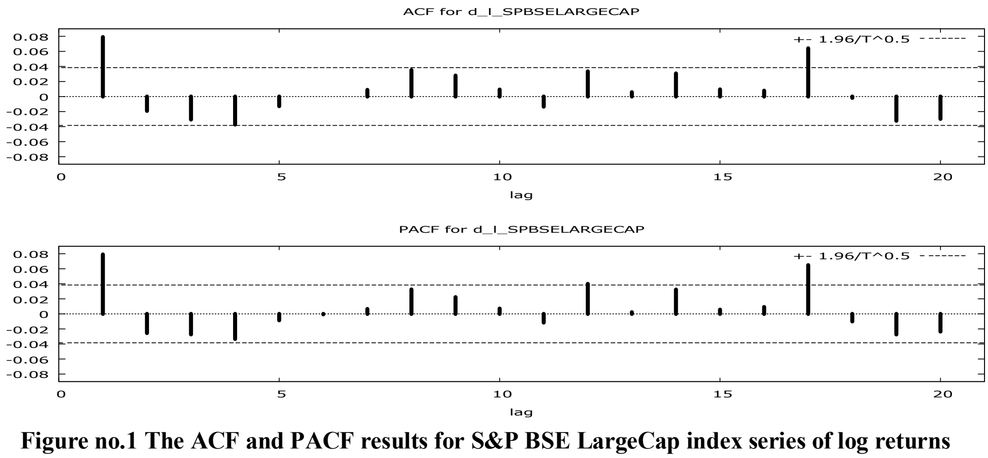

Figure no.1 The ACF and PACF results for S&P BSE LargeCap index series of log returns

Source: Author's computation

The series of S&P BSE LargeCap index started from base index point of 2825 in Jan 2005 and series returns are volatile completely as it has jumped over 4 times i.e. over 12000 index points in 15 years. Global financial crisis impact is quite visible in series return and dropped index 3000 points in less than a year. The volatility sketches indicate that any short term investment possibly created comparatively more loss than the gains and returns from investment. The following figure no.2 exhibits the behavior of S&P BSE LargeCap index movement as daily prices but also converted in stationary series of log returns.

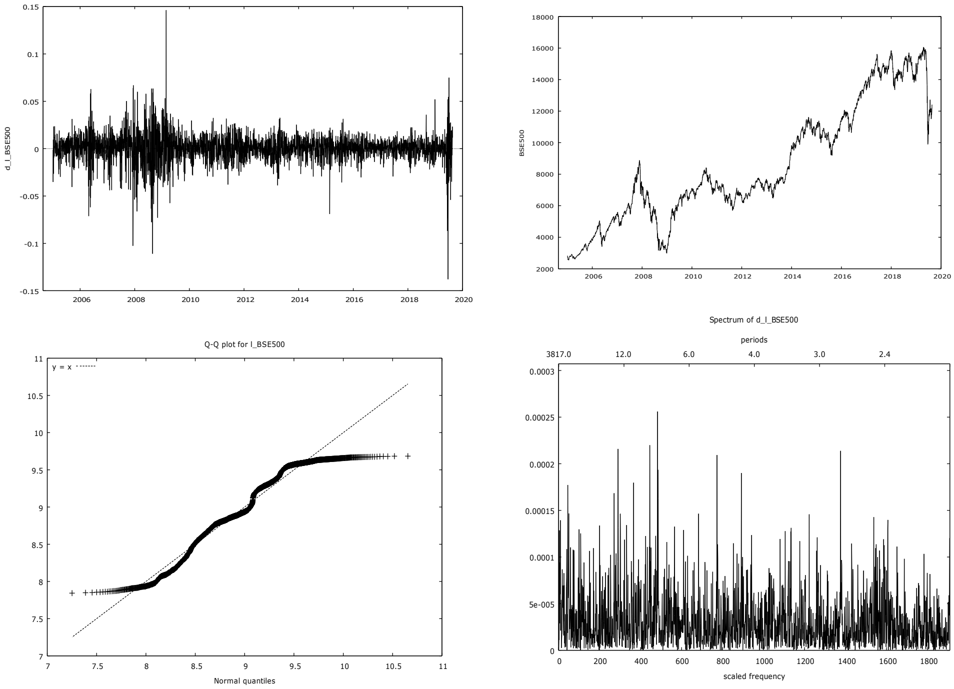

Figure no.2 The dynamics of S&P BSE LargeCap index
Source: Author's computation

Moreover the continuous rise of index immediate after global financial crisis has given new life and opportunity for investor confidence in S&P BSE LargeCap index and its activity sectors. Spulbar and Birau (2018) highlighted the fact that financial time series are characterized by time variation in mean and variance, which is the main reason for non-stationary dynamics. On the other hand, figure no.2 consists of four graphical pictures where the first represents original series returns, second indicates volatility sketches and stationary of series, third indicates the long fat tail which indicates leptokurtosis impact and last picture shows spectrum density (volatility effect) of S&P BSE LargeCap index series returns. The stationary graph presentation reveals the volatility magnitude which lasted up to 0.15 scales positively and around 0.12 magnitude scale negatively. Nevertheless there are many number of visible volatility sketches at upper side and lower side. The basic statistics indicates st_dev 0.01386 which means financial returns are not out of high risks. The mean and median are about zero which was expected since the indication of negative skewness and high degree of kurtosis which creates long fat tail effect (see fig1). Degree of minimum to maximum from zero is reversing the index (see table no.1).

Table-1 Summary Statistics for BSE500 (Jan 2005 to May 2020)

Mean	Median	Minimum	Maximum
0.00038775	0.0012582	-0.13789	0.14618
Std. Dev.	C.V.	Skewness	Ex. kurtosis
0.013886	35.812	-0.57962	11.279

Source: Author's computation

Autoregressive Conditional Heteroskedesticity model (ARCH), first introduced by Engle (1982) and further extended by Bollerslev (1986) and Nelson (1991). The GARCH (1, 1) model is not capable to explore the stylized facts in financial series but definitely it explores volatility in financial series returns. The GARCH (1, 1) model by Bollerslev (1986) is as follows;

$h_t = \omega + \alpha_1 u_{t-1}^2 + \beta_1 h_{t-1}$

Where h_t = represents volatility of S&P BSE LargeCap index, ω = represents constants, and $\alpha_1 u_{t-1}^2$ = represents ARCH (1) effect and $\beta_1 h_{t-1}$ = represents GARCH (1) effect.

It represents unconditional variance which must exist and thus it can be case where we find $\alpha_1 + \beta_1 < 1$ and for converting it into generates positive result, we require that $\alpha_0 > 0$. Only positive result will help to go ahead in progress since negative result will be useless. Positive result will indicate good news for market. And also gives an indication to precede further to employ asymmetry GARCH models.

The maximum return in series is 0.0939 and $\alpha_1 u_{t-1}^2 + \beta_1 h_{t-1}$= 0.118059 + 0.869686 = 0.987745 which is lower than 1 and positive. This indicates certain favorable signals to investors and also presence of strong volatility in financial series returns. This statistics suggests that financial series returns are significantly stationary. The sum of a + b <1 but it is most near to zero. It indicates high presence of volatility; furthermore the sum of b is greater than α_1 which was expected. It means the bad news generates long term volatility impact on financial series returns.

The volatility presence $h_t = \omega + \alpha_1 u_{t-1}^2 + \beta_1 h_{t-1}$ = 0.98857 in series return of BSE500. The importance of asymmetric and leverage effect in financial series return has given new vision to financial series return analysis and a very new criteria to investor for consideration before making investment. Exponential GARCH also known as EGARCH introduced by Nelson (1991) that takes long form and adds an additional term for leverage effect. This paper includes complete results for EGARCH and GJR GARCH including the density graph. Extended GARCH model introduced as EGARCH or Exponential GARCH by Nelson (1991) explores financial series returns in details and delivers results for asymmetry or leverage effect.

$\text{Log } h_t = \omega + \beta_1 \log h_{t-1} + \alpha_1 [\, \theta V_{t-1} + \gamma\{|V_{t-1}| - E|V_{t-1}|\} \,]$

To accept the null hypotheses of no leverage effect which indicated by (γ) in above model the following condition must fulfilled.

The gamma coefficient must be positive (+) otherwise alternate hypotheses will be accepted. It means gamma coefficient is negative; there is evidence of leverage effect in series. During the modeling of financial returns of S&P BSE LargeCap index we have considered significant level at 5% for EGARCH and GJR GARCH modeling. Here the y indicates asymmetry effect on series. The value for y should expected positive to accept null hypotheses of no presence of leverage effect. Otherwise the second hypotheses will be accepted i.e. presence of leverage effect. Leverage effect in financial series indicates that financial series returns are more volatile at downside and creates more volatile sketches and volatility clustering. In other words the listed stock becomes more risky to invest. Nevertheless, this also can be considered otherwise for the investors who look for long term investment in stocks. It creates an opportunity for investors to gain greater returns on investments if invested at right time of downside volatility. EGARCH model by Nelson (1991) fitted perfectly at significant level of 1%.

The value for $\gamma\{|V_{t-1}| - E|V_{t-1}|\}$ is non-zero and negative which was not fulfilling the null hypotheses of no leverage effect.

$\gamma\{|V_{t-1}| - E|V_{t-1}|\} = -0.0903640$

Furthermore the value for α_1 is 0.216334 which is much lower than the value for β_1 which is 0.975776. This statistics indicates that volatility is persistent or in other words it remains constant volatile at certain down level for long time. This situation takes long time to come over or block the investment for mean time. Non-zero and negative indicates that asymmetry series return has evidence of leverage effect in S&P BSE LargeCap index series returns and shocks are persistent. It also means that bad news creates more volatility than do good news. Table no.2 clearly indicates that return series exhibits volatility asymmetry. It indicates asymmetry impact of negative and positive shocks of the same magnitudes, in other words bad news or negative shocks creates more volatility in the market for long time than good news or positive shocks. This also means that good news or positive shocks stand always for short volatility persistence and self consume very quickly. EGARCH model by Nelson (1991) is limited to compute the impact of good and bad news in degree of magnitude. The impact of news on series return is estimated and modeled by using GJR GARCH type model by Glosten, Jagannathan and Runkle (1993). The asymmetry GARCH model (GJR) also indicates stylizes fact and impact of news in magnitudes. GJR – GARCH by Glosten, Jagannathan and Runkle (1993) can take following form;

$h_t = \omega + \alpha_1 u_{t-1}^2 + \beta_1 h_{t-1} + \theta I_{t-1} u_{t-1}^2$

To accept the null hypotheses of no leverage effect which indicated by (θ) in above model the following condition must fulfilled. The gamma coefficient must be negative (-) otherwise alternate hypotheses will be accepted. It means that if gamma coefficient is not negative; there is evidence of leverage effect in series. As we learned that if $\theta > 0$, we say that there is a leverage effect. If ($u_{t-1} > 0$), that has an effect of $\alpha_1 u_{t-1}^2$ on the variance and represents effect of good news on volatility, while bad news effects ($u_{t-1} < 0$) has an effect of $(\alpha_1+\theta) u_{t-1}^2$ on the variance. Furthermore the short term volatility persistence can be computed by ($\alpha_1 + \theta / 2$) where as we compute long term persistence by adding the Beta value in the above equation i.e. ($\alpha_1 + \beta_1 + \theta / 2$). GJR GARCH statistics estimates non-zero and positive gamma which indicates and supports the results of changing asymmetry and supporting leverage effect in series. Notable gamma value estimates 0.323941 which was expected negative for no leverage effect. The positive magnitude communicates at degree of 0.098279; this means that good news impact series return of S&P BSE LargeCap index at magnitude of 0.098279 scales. The

short term volatility persistence estimated 0.323941. The bad news impact on series is 0.42222.
GARCH and GARCH TYPE model estimations with Kernel density compare with standard normal distribution. All GARCH modeling estimation is followed by normal distribution considering OBS 3818 with VCV method.

5. Conclusions

This study does not cover the volume of trading along with the closing index of BSE-LARGECAP financial series. Data for S&P BSE LargeCap index collected from BSE, also known as the former Bombay Stock Exchange of India, website and covers the sample time period from January 2005 to May 2020 consisting 3818 daily observations. The basic statistics indicates negative skewness and over degree of kurtosis and creates leptokurtosis impact. Investors need to take note that the data statistics for standard deviation suggests that S&P BSE LargeCap index is no free from risk. Bollerslev (1986) GARCH (1, 1) model fitted very well on the series returns. It suggests presence of strong volatility. EGARCH estimated model indicates presence of leverage effect in the series os stock returns. It also was confirmed by GJR model designed by Glosten, Jagannathan and Runkee (1993). The result suggests that S&P BSE LargeCap index series return has evidence of leverage effect and takes long time to die out the negative shocks and creates more volatility in market. That means the positive shocks (at upper side) dissipates very quickly and do not stand long. This makes market riskier for beginner or makes investment block for long time to get recover. It means that bad news creates volatility for long time and it takes long time to die out at down side. On the other side it creates volatility for short time at upper side and dies out quickly. Investments made during this time may take long waiting to show the investment stock price. Similarly, the same data statistics also creates great opportunity to invest in S&P BSE LargeCap index if the investment made in long term volatility persistence, it increases chances to earn super profit returns in short time and create green prospects for investor community.

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