An Empirical Analysis of Volatility and Asymmetric Behaviour: Case of NSE and BSE

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Abstract:

The price, return and different events in stock market are uncertain but this uncertainty can provide insight for making investment decisions, if volatility is measured through appropriate model. In this research work, efforts are made to examine and compare the symmetric and asymmetric volatility in two major stock markets of India through the application of econometric models i.e. GARCH, TGARCH and EGARCH. Daily closing prices of NSE (Nifty-50) and BSE (Sensex) from 1st April 2010 to 31st March 2022 is used for the examination purpose. The results show that volatility in Indian market is persisted for a long time The asymmetric behaviour of volatility is also observed in Indian market. Findings are useful to design dynamic pricing, hedging and portfolio management strategies to all market participants.

Keywords: Stock Market Volatility, GARCH Models, Volatility clustering, TGARCH, EGARCH

Introduction:

Financial markets are considered as a barometer of economic growth of a country. The daily movements and fluctuations in the prices of financial instruments are reflected by these markets. The frequency at which prices of a security over a given period increase and decrease is understood as volatility. Volatility is calculated traditionally by taking daily changes in price and then annual standard deviation of these changes. High volatile stocks carry the risk of losing capital and investors avoid to invest in these stocks. It is generally assumed that increasing volatility is bad and difficult to establish link between volatility and economic growth. The financial markets organize the savings in more productive areas if economy is stable. The efficient allocation of savings and resources by financial sectors enhance economic efficiency. When financial markets work efficiently, the resources are moved to their best productive areas.

Volatility in stock market, is not surprising but it depends on overall performance of an economy. It is termed as random ups and downs in stock markets (Stock & Watson, 2004). The price, return and different events are uncertain and these are reflected by high level of volatility in concerned stock market (T. Bollerslev, 1986; Engle, 1982; Floros & Economics, 2008). Risk seekers can earn abnormal profits and risk averse investors can avoid their risk through proper measurement of volatility (Goudarzi & Ramanarayanan, 2011) (Ezzat, 2012). Volatility provides high returns with high risk. Before taking investment decisions, investors should probe into market volatility for risk management (Arouri, Jouini, & Nguyen, 2012) (Kyriakou, Pouliasis, & Papapostolou, 2016) (Moreira & Muir, 2017). The high volatility shows that the values of securities have more potential to fluctuate in a given time, while in case of low volatility, the values of security has low potential to fluctuate dramatically. The increased market return results in an increased volatility in the stock market (Dixit & Agrawal, 2020).

Indian stock market is very renowned as it is one of the oldest and most robust market in Asia. It is outperforming consistently and continuously from last decades. The expanded returns integrate it with other stock markets globally (Kundu & Sarkar, 2016). It has become popular among international investors to obtain benefits of diversification. (Xuan Vinh and Ellis, 2018). So, requirement is to re-investigate the nature and pattern of stock market volatility.

The present study investigates the movements in two major stock markets (BSE and NSE) of India that represent the whole Indian stock market and explores the existence of asymmetric behaviour there. Following the introduction, Section two includes review of literature, section three explains the techniques used to model the volatility, section four explains the interpretation of results, section five includes conclusion, section six future implications of the study and last section explains the scope for further research.

Literature Review:

The stock market return series display the feature of volatility clustering, leptokurtosis and leverage impact (Fama, 1965) and (Black, 1976). Modeling volatility is treated the most important concept in finance. Various econometric models are proposed by researchers to efficiently capture the characteristics of stock market behaviour. In this series ARCH and GARCH models are given by Engle (1982), and Bollerslev (1986) respectively and later on some advance versions of these models are propounded by researchers. The brief review of empirical findings of researchers globally in different time frames is as follows:

There are several methodological review conducted to find out the best model to measure the volatility, some concluded GARCH (1,1) model as the best model to describe and measure the stock market volatility and these studies also identified that leverage impact can be sufficiently measured through asymmetric GARCH models. (Gokcan, 2000) proved that GARCH (1,1) model was efficient in volatility prediction in emerging markets. The Athens stock market showed the asymmetric impact of news on stock market return when studied through GARCH (1,1) model (Siourounis, 2002). GARCH model was found as most suitable model to characterize the data in Hong Kong, which passes on all criteria and appears relatively consistent with the asymmetry existed in that data (Henry, 1998). (Liu & Morley, 2009) again studied the Hong Kong stock market from 2002-2007 by GARCH models and found it better than historical models. The study of US stock market volatility (conditional variance), by taking daily data of S&P 500 from January 01-01-1996 to January 29-01-2010 is done by using GARCH (1, 1) model and its advance models. Although the leverage effect was presented there, even then the symmetric GARCH model proved better to forecast conditional volatility in US market in comparison to asymmetric GARCH models (P Srinivasan, 2011).

1.1 Global Stock market and Volatility

Some studies that are conducted to compare the different asymmetric models report that EGARCH model is best to estimate the volatility in different markets. The prediction of volatility is done through asymmetric models in different countries (Gokcan, 2000) and (Miron & Tudor, 2010). When GARCH family models were applied on daily data of CMA index of Egypt and TASE-100 index of Israel to model the volatility in these markets, the EGARCH coefficient with expected sign was found significant showing asymmetric impact of news on volatility (Floros & Economics, 2008). The study of Ahmed and Aal showed that EGARCH model was the best to model the asymmetric volatility in stock market of Egypt from 1998 to 2009 (AbdElaal & Economics, 2011). But when the volatility of Khartoum, Cairo and Alexandria Stock markets was examined by using daily closing prices, GARCH-M model was found best to describe the conditional variance in both markets and leverage effect was found existed there (Abdalla, Winker, & Finance, 2012). A study volatility in India and China by using GARCH (1,1) model resulted that volatility in China is highly persisted than India. When the Impact of Eurozone debt crisis is studied on stock market of China, Hong Kong, Japan, and India the existence of clustering, leverage impact and persistence of volatility are proved by this work through EGARCH model used from 2005-2011.The features of clustering, existence of asymmetry and leverage impact are noted in stock returns of Japan, China, Hong Kong, and India (Singhania & Anchalia, 2013). When EGARCH and GJR-GARCH are applied on Nasdaq-100 index from 2000-2019, it is found that volatility shocks are quite persistent and index has leverage effect also exhibits clustering (Aliyev, 2019). In the same line, the asymmetries and persistent in volatility were observed for daily returns of Pakistan stock exchange between 2006 and 2020 (Umar, Mirza, Rizvi, & Furqan, 2023).

1.2 Indian Stock Market and Volatility

The same efforts are made by researchers in India also to study the nature of existed volatility in Indian stock market. Some studies are as follows:

When the time-varying volatility is modelled by taking the sample from NSE to check the impact of financial crises of 2008, the irregular and persistent volatility was found by both GARCH models (symmetric and asymmetric) that has been increased after this financial crisis (Tripathy & Gil-Alana Luis, 2015). A study showed the existence of time varying volatility in S&P Nifty for the time period from 2001-2010, in which the current volatility was found highly impacted by past volatility. Investors are able to forecast their returns under different market situations, by identifying the persistence of conditional volatility (Mehta & Sharma, 2011). When different models from simple GARCH (1,1) to advance versions of this model were used on daily data of SENSEX returns from 1996 to 2010, the symmetric GARCH model was found superior to measure the volatility (P. Srinivasan & Ibrahim, 2010). To find out the features of volatility in India, Srivastava used the data of SENSEX and NIFTY and reported that the leverage and ARCH effects were existed that can be measured by using GARCH models accurately (Srivastava, 2008). Again GARCH model is found superior to accurately measure and capture the features of volatility in S&P BSE 500 Index (2007-2016) with the features of volatility clustering and leverage impact existed in India (Susruth, 2017). When volatility is estimated by using data of S&P CNX500 index of NSE for 10 years (2003-2012) through GARCH, E-GARCH and TGARCH models, the results showed that the current volatility is highly impacted by past volatility in comparison to past shocks and news. Also, there exists a leverage impact in S&P CNX500 because the volatility is higher in case of negative shock rather than positive shock. It is also found the volatility shocks took long time to

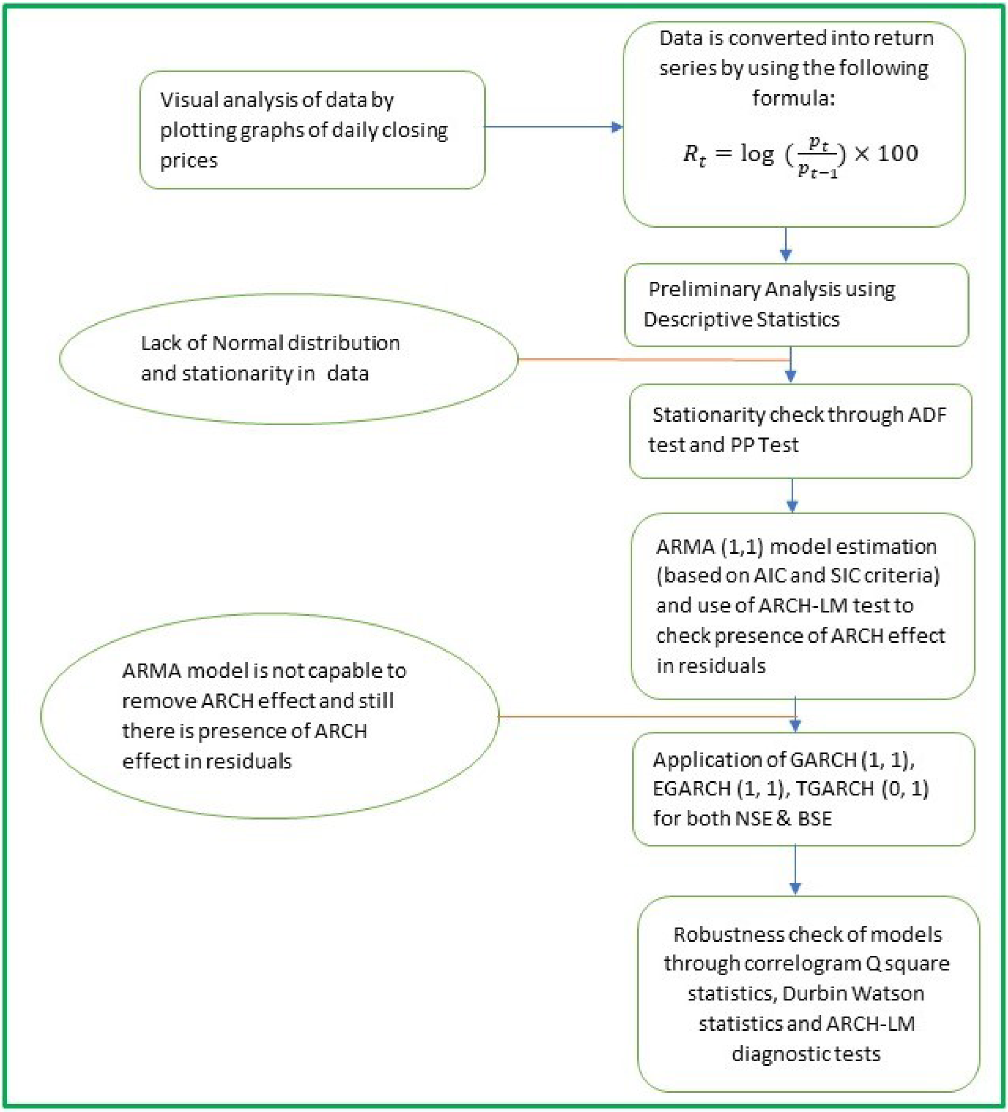

Figure 1: The step by step methodology

disperse and more prominent (Gupta, Jindal, & Gupta, 2014). The existence of volatility clustering (heteroscedasticity) is revealed in Indian market by using GARCH model. The stock returns and volatility in BSE Sensex was found positively correlated (Malepati, Challa, & Kolusu, 2019).

The leverage effects were found present in the study of S&P CNX Nifty Index (2003-2012). As per results, GARCH model measure the symmetric volatility while T-GARCH model measures the asymmetric volatility efficiently (Banumathy & Azhagaiah, 2015). P-GARCH model is found superior model to estimate the volatility in Indian market when analysis is done on closing prices of Sensex and Nifty (2011-2017) (Dixit & Agrawal, 2020).

The research Gap and Objectives

The literature on concerned topic shows that mostly studies are conducted on small sample size and there is no study on Indian stock market after Covid Era. Stock market volatility is a very dynamic issue which requires a comprehensive and regress research on large sample data to get complete understanding about nature, persistence and patterns of volatility in Indian stock market. So, the present study aims to understand the volatility in two major stock markets of India (NSE and BSE) through the application of GARCH family models and to check the presence of leverage impact of shocks in Indian stock market.

1. RESEARCH METHODOLOGY

1.1. Data and Sample Size

NSE is the third largest stock exchange on the basis of number of trades and one of the largest stock exchange in world on the basis of market capitalization (As per data maintained by World Federation of Exchange for the year 2022). The total market capitalization of NSE is US$ 3.27 trillion in Jan. 2023 (www.nseindia.com). NSE's flagship index, NIFTY50 is considered as a barometer of Indian market around the world. BSE is the oldest stock market of Asia with total market capitalization of₹ 2,62,37,776 Cr. (www.bseindia.com 6th April,2023) and its benchmark index is SENSEX. So, data from NIFTY-50 and SENSEX for the period 2010-2022 are collected from official websites www.nseindia.com and www.besindia.com respectively for this study. These two indices are used by researchers in their study as a representative of whole Indian stock market (Malepati et al., 2019) (Dixit, Agrawal, & Agarwal, 2022) (Karmakar, 2005). The daily closing prices of both indices except legal holidays and days for which no transactions are performed are taken. A total number of 2979 daily observation are included in the sample as per Table 1.

1.2. Volatility Measurement Technique

The features of auto regression and volatility clustering of a time series data makes it possible to predict its future values (Karmakar, 2005). The traditional model used to analyses the time series data does not provide desired results due to non-constant variance. Autoregressive Conditional Heteroskedasticity (ARCH) model was given by Engle (1982) for modeling time varying conditional variance for the first time. To model the volatility through ARCH requires many parameters and assumes constant variance also. This ARCH model can be applied on stationary data by following equation:

$$\sigma^2 t = \alpha_0 + \alpha_1 \; e^2 t\text{-}1 + \ldots\ldots + \alpha_n \; e^2 t\text{-}n \quad \text{(i)}$$

Here σ^2 t is conditional variance that depends on squared value of error terms and α_1 *up to* are unknown coefficients of ARCH process.

The Symmetric GARCH Model:

The problem of large parameters and constant variance was solved in 1986 when Bollerslev and Taylor developed a GARCH (Generalized Autoregressive Conditional Heteroskedasticity) model where variance depends on its lagged value and on squared residuals. GARCH models considered to be the chief methodologies that are useful to model the stock market volatility (Abbas Rizvi, Naqvi, Bordes, & Mirza, 2014). This method to model the volatility of stocks is most suitable when data is large (Engle, 1982) (T. Bollerslev, 1986) (Leung, Daouk, & Chen, 2000).

In present work, GARCH (1,1) model is applied to study the pattern of volatility in NSE and BSE markets as this model sufficiently measure the volatility clustering in data (Brooks & Burke, 2003). It is described by following equations:

Mean Equation: $r_t = \mu + \varepsilon_t$ (ii)

Variance Equation:

$$\sigma_t^2 = \alpha + \alpha_1 \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 \text{ (iii)}$$

Where

α is constant *where* >0 *and* $\alpha_1 \geq 0$ *and* $\beta_1 \geq 0$,

$r_t = return\ of\ the\ asset\ at\ time\ t$

$\mu = average\ return$

$e_t = residual\ returns$ at time t

$\alpha_1 \varepsilon_{t-1}^2$ =ARCH term (Information about previous volatility as measured by previous period squared residuals from mean equation)

$\beta \sigma_{t-1}^2 =$ GARCH term (Long term memory of volatility as lagged values of conditional variance

The reported measures the extent of today's shock impacts the volatility of next period (Campbell, Lo, MacKinlay, & Whitelaw, 1998). The volatility is assumed to be highly persistent if $\alpha_1 + \beta$ is close to one (Caiado, 2004). The rate of dying out of any shock in the volatility is (1-. If the sum of and is equal to one or more than one then, it indicates about existence of effect of any shock permanently. It may be possible due to non-stationarity of the series. If the total of ARCH and GARCH term is equal to one, it is termed as unit root. The total must be less than one. This condition is imposed in applying GARCH model that all coefficients should be positive. It is known as non-negativity constraints of GARCH model.

The basic GARCH model is able to account for volatility clustering and leptokurtosis conditions of time series. It is not able to consider the leverage impact in data. To overcome this drawback, advance versions are developed as T-GARCH and E-GARCH models.

Threshold GARCH (TGARCH) Model:

Glosten, Jagannathan and Runkle (1993) and Zakoian (1994) developed and used the TGARCH model to measure leverage impact of financial assets. This model is also known as GJR model after the names of its authors. The GJR model is sufficient to capture the volatility clustering and leverage impact in data (Bekaert, Engstrom, & Ermolov, 2015). The TGARCH (1,1) model can be specified as follows:

$\sigma^2 t = \omega + \alpha_1 e^2_{t-1} + \gamma d_{t-1} e^2_{t-1} + \beta_1 \sigma_{t-1}$ (iv)

Where d_{t-1} represents dummy variable

γ is Parameter of asymmetry.

According to this model, the impact of good news (ε_{t-1} $\mathbf{0}$) and bad news (ε_{t-1} $\mathbf{0}$) are different on conditional variance. The impact of good news is and bad news . If γ is significant and positive in the fitted model, then it indicates about greater effect of bad news on $\sigma^2 t$.

The Exponential GARCH (E-GARCH) Model:

The asymmetric impact of shock to conditional variance is captured along ensuring the positive variance always by EGARCH Model that is proposed by (Nelson, 1991). In this model, the conditional variance is transformed into natural logarithmic form by following equation:

$$Ln(\sigma^2 t) = \omega + \beta 1 Ln(\sigma^2_{t-1})$$

$$+\alpha 1 \left\{ \left| \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \right| - \sqrt{\frac{2}{\pi}} \right\} - \gamma \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \qquad \text{(v)}$$

Where γ is the coefficient of asymmetric term. When γ is positive, indicates about symmetric impact but when γ is negative, it indicates about asymmetric impact of news (Nelson, 1991) (T. J. C. R. p. Bollerslev, 2008).

1. Results And Interpretation

1.1. Descriptive Statistics

The daily closing prices movements for both the markets are displayed in Figure 2. It is evident from the plot that data is non-stationary. Figure 3 of the daily returns of both indices depict the changes in volatility over time and volatility clustering. Then both return series are filtered through descriptive statistics (Table 2). The mean value is 0.040103 and 0.040196 for both indices that is near to zero and the risk indicators (standard deviation) for the markets is 1.101646 and 1.099098. It indicates that NSE is slightly riskier than BSE market. The Skewness and kurtosis values are considered as extreme values when higher than one and three respectively (Rohatgi & Saleh, 2015).The return series are

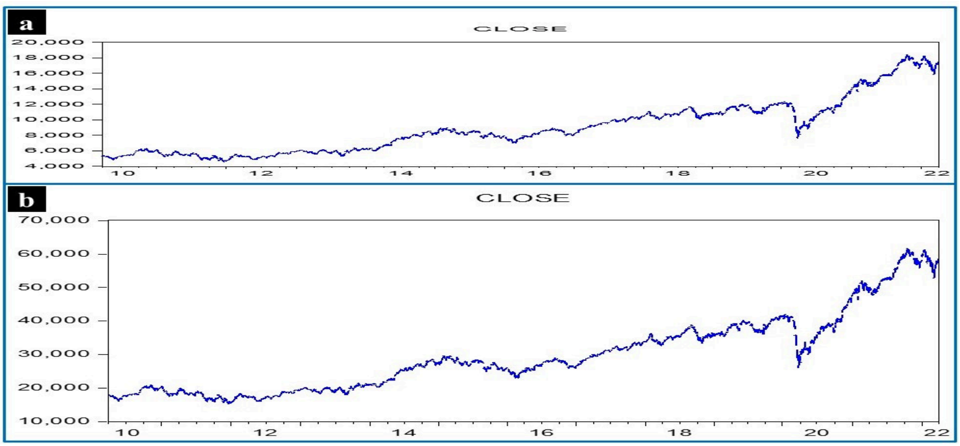

Figure 2 (Closing prices of NIFTY-50 and SENSEX)

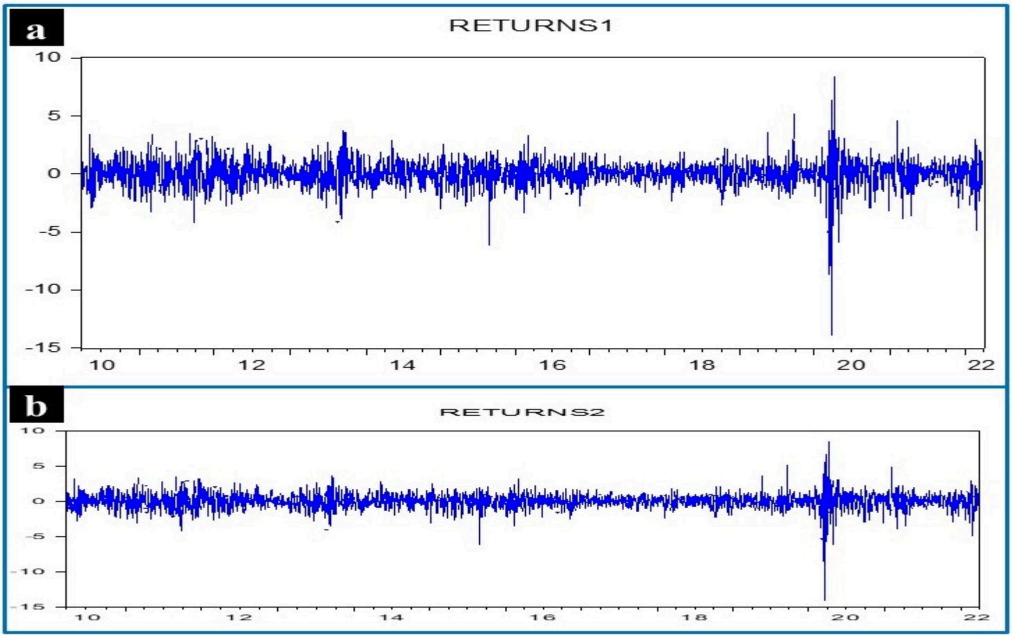

Figure 3. (Return series of NIFTY-50 and SENSEX

negatively skewed, demonstrating that the series is non-symmetric and there is higher chances of large negative returns than positive returns in both markets. Further, the Kurtosis value shows that data are having thick tails and higher peaks (Levendis, 2018). It is leptokurtic distribution in comparison to the normal distribution (Emenike, 2010) (Ezzat, 2012). It is also established by Jarque–Bera statistics that data is not normally distributed (Jarque & Bera, 1987). It becomes clear from descriptive statistics that further examination is required through appropriate econometric model.

1.2. Stationarity Test

To check the stationarity of data, the ADF (Augmented Dickey and Fuller) test and PP test (Phillips- perron Test) are used. The results of both tests reject the null hypothesis of data having unit roots because the t-statistics value is less than 0.05 as shown in Table 3.

1.3. ARMA Modeling

To analyse this data properly, an appropriate econometric model ARMA (Box-Jenkins Methodology) is applied. ARCH-LM test is performed to test the heteroscedasticity in residuals of both

Table 1. Name of Indices, Data Sources and Time period of the study

Name of Stock market	Indices	Data Sources	Time period of study
NSE	NIFTY-50	www.nseindia.com	01-04-2010 to 31-03-2022
BSE	SENSEX	www.bseindia.com	01-04-2010 to 31-03-2022

return series (Joshi, 2010). Table 3 exhibits the results of ARCH-LM test. When the data shows the features of volatility clustering, the ARMA model that assumes conditional variance as constant is not able to capture the nonlinear characteristics of data (Zivot, 2009). Due to presence of volatility clustering, stationarity at level and ARCH effects in residuals, ARCH/ GARCH models are assumed to be suitable model to study the volatility patterns (Predescu & Stancu, 2011) (Gujarati & Porter, 2009).

1.4. GARCH (1,1) model estimation

After confirming volatility clustering in data through graphs, stationarity by adopting ADF and PP test, presence of heteroscedasticity through ARCH-LM test, this study focuses to model the volatility through GARCH model. The results of GARCH model are given in Table 4. All coefficients i.e. constant, ARCH and GARCH term of variance equation for the GARCH (1,1) model were found significant and exhibited the anticipated sign. The ARCH term value explains the current news impact on market volatility (Campbell et al., 1998), while the GARCH term depicts the impact of historical volatility and volatility persistence. The coefficient of ARCH term (0.087898) was lesser than GARCH term (0.893447) for NSE that shows that current market volatility in NIFTY-50 is highly impacted by past information in comparison to current news (Mehta & Sharma, 2011). The present volatility in NSE market is mainly due to past shocks and the impact of current news is very little on this volatility. The total of coefficients of ARCH and GARCH terms is very close to unity (0.981345) that indicates the long memory and highly persisted shocks to the conditional variance (Karmakar, 2007) (Franses & Van Dijk, 1996; Kumar & Singh, 2008).

Table 2. Descriptive Statistics (Period: April 2010 to March 2022)

Descriptive Statistics	NIFTY-50	SENSEX
Mean	0.040103	0.040196
Median	0.062627	0.065209
Maximum	8.400291	8.594739
Minimum	-13.90375	-14.10174
Std. Dev	1.101646	1.099098
Skewness	-0.966082	-0.977415
Kurtosis	16.93083	17.99006
Jarque-Bera statistics (Probability)	24543.85 (0.00) *	28355.93 (0.00) *
Total observations	2978	2978

Source: Authors' Calculation

In the same way ARCH term value for SENSEX (0.085659) was less than GARCH term (0.896276), displaying the same result as NIFTY50 that market volatility in BSE is largely dependent on past information than current news. When volatility is high, it indicates the higher chances of earning profits as well as inefficiency of the market (Mittal, 2012). Even then it will be mean reverting as it is close to unity. That indicates the feature of volatility clustering in NSE market.

1.5. The Asymmetric Model Estimation (TGARCH and EGARCH)

The symmetric GARCH model (GARCH 1,1) failed to explain the difference in impacts of news on volatility (Nelson, 1991), (Schwert, 1990) and . It is the assumption of this model that both types of news (good and bad) are having same impact on volatility. To know this leverage impact of news, TGARCH and EGARCH models are used.

When TGARCH (1,1) model is estimated, the ARCH coefficient was found negative, that is contrary to its non-negativity constraint (Irfan, Irfan, & Awais, 2010). So, TGARCH (0,1) model is estimated for NIFTY50 and SENSEX. For NIFTY50, the TGARCH coefficient (0.155072) was positive and significant that shows that news has asymmetric impact on market volatility. For BSE market also, the TGARCH coefficient (0.152305) was positive and significant, indicating asymmetric impact of good and bad news on BSE market volatility.

In the same way EGARCH coefficient (--0.11535) for NIFTY50 is negative that shows that bad news has more impact on market volatility in comparison to good news of same magnitude (Chen & Ghysels, 2011). The same results were provided by SENSEX EGARCH coefficient (-0.11666) that market volatility is more impacted by bad news than good news having same magnitude. Both markets show the presence of asymmetric volatility (Aliyev, 2019).

1.6. Robustness check of models

The Q-squared (12) test and ARCH-LM test are performed to test the fitness and suitability of GARCH models. The result of these test proves the absence of ARCH effect after estimating the

Table 3. Unit Root tests and ARCH-LM test:

Test	NIFTY-50	SENSEX
ADF test at Level	-0.54.08142 (0.000) *	-0.54.23322 (0.000) *
PP test at Level	-54.08765 (0.000) *	-54.23356 (0.000) *
ARCH-LM F-stats.	97.63112 (0.000) *	97.91909 (0.000) *

Note: * (p<0.05)

Source: Authors' Calculation

GARCH models because the probability value is more than 0.05 indicating insignificant Q-squared and ARCH-LM statistics. The Durbin Watson stats also proved the fitness of all models. The results of all diagnostic tests proved the fitness of estimated model.

Table 4. Model Estimation results for NIFTY 50 and SENSEX

Coefficient	NIFTY-50			SENSEX		
	GARCH (1,1)	TGARCH (0,1)	EGARCH (1,1)	GARCH (1,1)	TGARCH (0,1)	EGARCH (1,1)
Mean Equation Constant	0.07108*	0.036784	0.031296*	0.073001*	0.039116*	0.033025*
AR	-0.06127	-0.13778	0.063823	-0.062622	-0.14253	0.035728
MA	0.120802	0.209905	0.007291	0.121985	0.21242	0.033854
Variance Equation Constant	0.022578*	0.030189*	-0.1003	0.021486	0.0295*	-0.10033*
ARCH (α)	0.087107*		0.127238*	0.085023*		0.126299*
GARCH (β)	0.894403*	0.893439*	0.972236*	0.897061*	0.894881*	0.971903*
TGARCH		0.155072*			0.152305*	
EGARCH			-0.11535*			-0.11666*
R-squared	-0.00339	-0.00441	-0.00386	-0.003766	-0.00446	-0.00406
Adjusted R-squared	-0.00407	-0.00509	-0.00453	-0.004441	-0.00513	-0.00474
Log Likelihood	-4107.75	-4052.39	-4045.48	-4082.631	-4026.68	-4020.24
Durbin-Watson stat	2.101255	2.12912	2.125025	2.106068	2.129946	2.127453
Akaike info criterion	2.76369	2.726498	2.722523	2.746813	2.709225	2.705569
Schwarz criterion	2.775781	2.738588	2.736628	2.758903	2.721315	2.719674
ROBUSTNESS TESTS						
(12) stat (Probability)	14.104 (0.294)	12.351 (0.418)	11.691 (0.471)	14.049 (0.298)	12.545 (0.403)	13.37 (0.343)
ARCH-LM F-statistic (Probability)	2.153706 (0.1423)	2.653443 (0.1034)	1.717945 (0.1901)	2.155157 (0.1422)	2.708692 (0.0999)	2.041433 (0.1532)

Note: * ($p<0.05$)

Source: Authors' Calculation

2. CONCLUSION

In this work, efforts are made to study the nature of volatility in Indian stock market. For that data for two representative indices, NIFTY-50 and SENSEX is collected for the period of 12 years. The analysis of descriptive statistics shows the characteristics of negatively skewed, highly kurtosis with fatter tails and non-normal distribution of return series. The mean and median values are near to zero suggesting mean returning and volatility clustering nature for both markets. Box-Jenkins Methodology is adopted to further analyse the return series but incapable to handle the ARCH impact from financial data. GARCH (1,1) model is successfully implemented to extract meaningful information that there exists volatility persistence in Indian stock market. GARCH (1, 1) model is capable to efficiently measure the market volatility and it is consistent to the finding of Madhusudan (2005), Karmakar (2007) and (Gokcan, 2000) study but GARCH (1, 1) model is not capable to measure the leverage impacts of news (Karmakar, 2005, 2007). Based on the past study, it can be said that GARCH (1, 1) model explains the volatility with symmetric information and the asymmetric GARCH models are appropriate in case of asymmetric information (Banumathy & Azhagaiah, 2015) (Okičić, 2015). The findings of this study show the presence of long memory and highly persisted shocks to the conditional variance in NSE and BSE markets. Both markets are highly correlated and following the same trend (Dixit et al., 2022). It is also clear from the results that volatility in Indian market react differently to good and bad news of same magnitude (Banumathy & Azhagaiah, 2015), (Srivastava, 2008). The robustness of model is verified through different diagnostic tests i.e. Durbin Watson stat, the Q-squared stat and the ARCH-LM test that prove the fitness of the model. It is observed that coefficients are same for both market showing a high degree of correlation between these two markets. The planning of investment strategies for one market will be suitable to other market too. In this type of market environment, portfolio investment may be used to hedge the risk.

3. FUTURE IMPLICATIONS OF THE STUDY

The present work is helpful for investors in their investment decisions by providing insight about volatility in Indian stock markets. They would be aware about increasing risk associated with increasing volatility in present era of global integration and financial liberalization. The policy makers and market analysers are able to predict the market movements as the sum of ARCH and GARCH is less than one, representing mean returning trends of both markets. The finding shows that both markets (NSE and BSE) are correlated markets. So, through investment in non-correlated markets, investors can get benefit of portfolio diversification by reducing risk and increasing returns.

4. SCOPE FOR FURTHER RESEARCH

Present study has made a great contribution in analysing stock market volatility but it is not free from limitations that lead to further research. In this work, symmetric as well as asymmetric models are adopted to study the volatility patterns in Indian market. To get a wider aspect of volatility, some advance models like NARDL model on sectoral indices to may be adopted to go deeper into markets.

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