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Market Volatility & Information Asymmetry: Evidence from Indian Market

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Abstract

The stock market is a vital component of a nation's global economic endeavours. The emergence of COVID-19 has had an unprecedented impact on the whole global financial sector. The global impact of the COVID-19 respiratory disease caused by the corona virus has resulted in widespread devastation due to the absence of immunisations or sophisticated medical interventions. The World Health Organisation (WHO) has officially classified this disease as a pandemic, causing widespread concern and attention to human health globally. The virus initially caused astonishment in India when the country announced its first incidence on January 30, 2020, in Kerala. Since then, the spread of the virus has not ceased. The Indian economy has been put on hold ever since Prime Minister Shri Narendra Modi imposed a state wide lockdown to curb the spread of the virus. Given the current COVID-19 situation, it is imperative to forecast and anticipate volatility in the field of finance. Forecast the level of instability in the Indian stock market by examining the volatility of NIFTY returns. The analysis utilises the daily closing values of indices from 1st April 2019 to 31st March 2022, sourced from the official websites of the corresponding stock market. The study employs both symmetric and asymmetric models of Generalised Autoregressive Conditional Heteroskedastic (GARCH), as well as GARCH family models like EGARCH and TGARCH, to examine the goals of the state. This study empirically examines the influence of the COVID-19 pandemic on the Indian stock market. Evidence indicates that the stock market in India has encountered fluctuations during the era of the pandemic. Upon analysing the results, the study finds that the return on the indices was higher in the pre-COVID-19 period compared to the period during COVID-19.

***Key Words**: Covid-19, Volatility, NSE, BSE, and GARCH Family Model*

Introduction

The stock market is a vital component of a nation's global economic endeavours. The emergence of COVID-19 has profoundly impacted the whole global financial sector in an unprecedented manner. The outbreak of the coronavirus originated in December 2019 in the city of Wuhan, China. The global impact of the COVID-19 respiratory disease caused by the coronavirus has been severe, given there are now no vaccinations or improved treatments available. The World Health Organisation (WHO) has officially classified this disease as a pandemic, causing widespread concern and attention to human health globally. The onset of this virus in India left the country astounded when the first case was announced on January 30, 2020, in Kerala. Since then, the spread of the virus has not ceased. The Indian government implemented a Janta curfew on March 22, 2020, followed by a lockdown policy on March 24, 2020, in order to enforce social separation and mitigate the spread of the breakouts. Since Indian Prime Minister Shri Narendra Modi declared a statewide lockdown to curb the spread of the virus, the Indian economy has been at a standstill. In order to control this lethal illness, the only options available are practicing social distancing, keeping proper hygiene by sanitising, and bolstering one's immunity. Volatility arises from uncertainty, which may lead to favourable outcomes, but also carries the chance of bad events. Stock price fluctuations generally hinder market efficiency resulting from excessive volatility, perhaps leading to market crashes or crises. Higher volatility is characterised by a wider dispersion of values, while lower volatility exhibits less spectacular fluctuations but still experiences changes in value over time. Given the current COVID-19 situation, it is imperative to forecast and anticipate volatility in the field of finance. Instability Anticipate the level of instability in the Indian stock market by examining the volatility of NIFTY returns. The study employs both symmetric and asymmetric models of the Autoregressive Conditional Heteroskedastic (ARCH) process to incorporate the dynamic nature of volatility over time, as initially suggested by Engle (1982). Additionally, Generalised Autoregressive Conditional Heteroskedastic (GARCH) models were subsequently developed by Bollerslev (1986). The GARCH family encompasses models such as the EGARCH model and the TGARCH model. Nelson (1991) introduced the EGARCH models. Zakoian (1994) introduced the Threshold GARCH (TGARCH) model. This is an alternative volatility model that permits asymmetric effects. The TGARCH model is widely regarded as the most appropriate method for assessing the effects of both positive and negative shocks on volatility. The analysis utilises the daily closing values of indices from 1st April 2019 to 31st March 2022 as its foundation. This article aims to empirically analyse the influence of COVID-19 on the Indian stock exchange. India has encountered fluctuations in economic and social conditions throughout the duration of the pandemic. Upon analysing the outcomes, the study finds that the return on the indices was larger in the pre-COVID-19 period than during COVID-19.

The remaining material is divided into 6 Section. Section II provided an overview of the literature reviews. Section III pertains to the analysis of data and the duration of the investigation. Section IV provides an account of the methodology used. Section V examines the outcome, while Section VI concludes with a summary and suggestion.

Literature Review

Hwang et al. (2001) analyse the Threshold ARCH (1) processes. They do asymptotic inference using the daily time series index from January 3, 1997, to May 31, 1999. The study employs the ARCH family model and derives parameter estimates using the least-squares method. Additionally, it obtains pertinent limit results. It has been discovered that the Korean financial time series adheres to the martingale Central Limit Theorem (CLT) and the ergodic theorem. To stabilise the variances, a Log-transformation is performed. Subsequently, the Dickey-Fuller (DF) test is used to each series. The study determined that TARCH (1) utilises the mean absolute percentage errors (MAPE) as a metric to assess the accuracy of a model. Gazda et al. (2003) analyse the asymmetric impact of the Slovak share index (SAX) using time series data from 1997 to 2002, consisting of 1173 daily observations. The study employs ARCH family models. SAX is found to adhere to the martingale process. The paper presents findings on the leverage effect in stock returns using EGARCH and TARCH models. Ultimately, they assert that the EGARCH model is the most appropriate choice for volatility forecasting compared to other models. In their study, Conrad et al. (2003) examine the suitability of the fractionally integrated (asymmetric) PARCH model for ten US bilateral exchange rates. They use daily time series data from 1st January 1990 to 18th November 2003, consisting of 3,621 observations. The study focuses on the stable and integrated (A)PARCH models. The study demonstrates that the fractional deference parameter and power transformation exhibit striking similarities across countries. The study indicates that fluctuations in the variance are gradually attenuated, but eventually cease. Estimating inside the sample is strengthened by evaluating forecasts outside of the sample. The study conducted by Duan et al. (2004) focuses on developing an analytical approximation formula for pricing European options using GJR-GARCH and EGARCH models. The researchers also discuss the use of Monte Carlo simulation as a method for determining the option price. The study use the GARCH family of models. The study demonstrates the expansion of the current collection of approximation formulas for the GARCH model. The study discovered that the GARCH option pricing model may be efficiently computed for European option prices in online applications using the approximation formula. In Malmsten's (2004) study, an estimated EGARCH model is analysed using multiplier type tests. The analysis includes comparing the EGARCH model against a higher-order model and assessing the constancy of parameters, which are parametric in nature. The study included many methodologies to assess the EGARCH model in comparison to the GARCH model, including the LR test, Encompassing test, and pseudo-score test. The study concluded that, in practical applications, it is advisable to prioritise the use of robust versions of our tests over non-robust ones. The study proposes using conventional methods to assess the appropriateness of an estimated EGARCH (p, q) model. Taylor (2004) analyses the prediction of volatility using a method called smooth transition exponential smoothing. The study focuses on eight stock indices and uses daily time series data from December 30, 1987, to August 30, 1995, covering a total of 2000 trading days. The study employs the model of time-varying parameters in smooth transition GARCH models, which can also serve as transition variables in the novel smooth transition exponential smoothing approach. The study mostly concentrated on forecasting for the immediate future. The paper proposes using the novel STES approach for multi-step-ahead forecasting. The study demonstrates the utilisation of fixed-parameter exponential smoothing and various GARCH models. In this study, Chen et al. (2005) analyse six different models used to predict the values of the main market indices in five ASEAN equities markets (Malaysia, Singapore, Thailand, Indonesia, and the Philippines) during the periods before, during, and after a crisis. The analysis utilised the time series of daily closing data from 2 January 1992 to 12 August 2002, obtained from the financial data provider Bloomberg. Additionally, the study encompasses the analysis of log index relatives. The study used six estimate models, namely RW, OLS, GARCH (1, 1), ARCH (1, 1)-M, TARCH (1, 1), and EGARCH (1, 1) models. The analysis identified TARCH, OLS, and ARCH-M as the most effective models for the Asian markets during the pre-crisis time. For the crisis period, ARCH-M and RW were found to be the best models, while TARCH and EGARCH were determined to be the most suitable models for the post-crisis period. The several iterations of the GARCH model effectively reflected the volatility of the fluctuating returns. According to the study, it is not advisable to rely on a single forecasting model to predict future stock returns, as the optimum approach involves considering the market characteristics of the given market. In his study, Jing-rong (2007) analyses the combination of stock market volatility projections using an Exponentially Weighted Moving Average (EWMA) technique. The analysis is based on the daily closing data of the Shenzhen Stock Exchange, collected from 2 January 2001 to 30 July 2006. The study employs several methods, such as the Generalised Autoregressive Conditional Heteroskedastic (GARCH), Exponential Generalised Autoregressive Conditional Heteroskedastic (EGARCH), and stochastic process models. These methods are combined and supported utilising the Mean Absolute Percentage Error (MAPE) for weighting. The study demonstrates that utilising a combining approach with a small λ value may prove to be unproductive in cases where there is a significant disparity in accuracy between the individual forecasts. In their study, Mun et al. (2008) analyse the Leverage Effect and Market Efficiency of the Kuala Lumpur Composite Index. They use the weekly closing prices of Malaysia stock market indices from January 9, 2004, to June 8, 2007, sourced from Bursa Saham Malaysia. The study employs EGARCH and assesses its efficacy through the application of Augmented Dickey-Fuller (ADF). According to the study, the market behaves in a random manner and does not respond to either positive or negative news, as predicted by behavioural finance theory. The study demonstrates that the EGARCH model indicates that the stock price has already incorporated all relevant information in the market. No news has the ability to influence the fluctuations in stock prices. It indicates that the KLCI adheres to the weak form theory. In his study, Chang Su (2010) analyses the volatility of the Chinese stock market in relation to other stock markets during the crisis period. The study uses daily time series data from January 2000 to April 2010, specifically focusing on the Hang Seng, H-shares, A-shares, and B-shares. The dataset consists of 2215 observations for each stock market. The study employs the GARCH (1, 1) model and the EGARCH (1, 1) model. The primary aim of this study is to investigate the risk behaviour in the Chinese stock markets and assess the predictability of stock market returns through an analysis of long-term volatility. The study indicates that the EGARCH model is more suitable for modelling the volatility of Chinese stock returns based on the sample data, compared to the GARCH model. The study reveals that, during the crisis time, negative news had a more pronounced impact on the Chinese stock market compared to positive news. Alam et al. (2012) analyse the GARCH, EGARCH, PARCH, and TARCH models in comparison to an AR model and an ARMA model using secondary data as a benchmark. The requested data pertains to the exchange rates between the Bangladeshi Taka (BDT) and the U.S. Dollar (USD) from July 03, 2006, to April 30, 2012, encompassing a total of 1513 days of observations. The presence of GARCH(-1) indicates that the volatility of risk is highly influenced by previous squared residual terms, whereas the past volatility of the exchange rate has a large impact on the current volatility. The TARCH model demonstrates that all the coefficients of the terms are included in the variance equation. The study concluded that the GARCH model outperforms other models when considering transaction costs. Based on the statistical performance findings within the sample, both the ARMA and AR models are considered the best models. However, when considering out-of-sample data, the study found that the TARCH model is considered the best model in the absence of transaction costs. In 2013, Goudarzi aimed to analyse the market efficiency in the Indian stock market by studying specific characteristics of asset returns, such as mean reversion, volatility clustering, fat tails, and long memory. This was done by utilising statistical and econometric models, including the ADF test and GARCH family models, on daily time series data from 2000 to 2010. The market is deemed inefficient as a result of the influence of multiple factors. Hence, in order to enhance market efficiency and ensure the smooth dissemination of information to market players, policymakers must carefully evaluate these aspects to mitigate any speculative activity in shares that may arise from crashes or crises. Monfareda et al. (2015) conducted a study on noise cancelling in volatility forecasting. They used an adaptive neural network filter based on secondary daily closing index data obtained from the Yahoo Finance database (finance.yahoo.com). The data covered the period from 4/2/2007 to 12/31/2010. The paper demonstrates that utilising data from non-stationary and random walk processes enhances the efficacy of a parallel forecaster model, namely the GARCH (1,1) model in this instance. The study indicates that the performance of threshold noise filtering remains consistent across many economic scenarios, similar to other forecasting methods like neural networks or hybrid models. Singh, G., (2017) analyses the fluctuation patterns of the Indian stock market.

The study focuses on utilising the time series data analysis technique to examine the volatility of the NIFTY index of NSE. The study collected daily data from January 2000 to December 2014, resulting in a total of 3736 data points for analysis. The paper examines the superiority of ARCH family models over conventional OLS models and compares the GARCH, EGARCH, and TARCH models based on AIC and SBIC criteria. The study discovered that this information would be valuable to investors since it presents proof of the fluctuating nature of stock market volatility in India. Investors strive to achieve more profitability and reduce investment risk. The study indicates that the main factors contributing to this phenomenon in the Indian market are significant speculative trading, a low level of market depth, and the presence of price limitations.

Objective of the Study

To examines the volatility forecasting of Bombay Stock Exchange (BSE) & National Stock Exchange (NSE).

III. Data & Study Period

The study examines secondary sources of data. Data encompasses the daily closing value of two prominent Indian capital market indices, namely NSE and BSE. The daily data is sourced from the official website of the respective entity. Data is gathered over the time span of April 1, 2019 to March 31, 2022. In this analysis, we are examining a time span of three fiscal years, distinguishing between the period before the onset of the Covid-19 pandemic and the period during the pandemic.

IV. Methodology

The study employs different symmetric and asymmetric models of the Autoregressive Conditional Heteroskedastic (ARCH) process to incorporate the dynamic aspect of volatility over time, as initially suggested by Engle (1982). The Generalised Autoregressive Conditional Heteroskedastic (GARCH) model is the primary model used to analyse stock market volatility. The current work examines GARCH family models, specifically the EGARCH model and the TGARCH model. Before doing these tests, the volatility was evaluated based on the return. To do this, the daily returns were determined. The index is computed by taking the logarithm of the first difference of the daily closing price, as shown below.

$$R_t = \log \frac{P_t}{P_{t-1}}$$

Where R_t is the logarithmic daily return on the Indian stock market index for time t, pt is the closing price at time t and p_{t-1} is the corresponding price in the period at time t-1.

Autoregressive Conditional Heteroskedasticity (ARCH) Models

The Autoregressive Conditional Heteroskedasticity (ARCH) is a statistical model developed by Engle (1982) to account for the time-varying character of volatility. In the ARCH model, heteroskedasticity, or uneven variance, does not exhibit an autoregressive structure. This implies that the observed heteroskedasticity over different periods is associated, indicating the presence of the ARCH effect and volatility clustering in time series data. To test the ARCH of the following Equation:

$$u_t^2 = \gamma_0 = \gamma_1 u_{t-1}^2 + \gamma_2 u_{t-2}^2 + \ldots + \gamma_p u_{t-p}^2 + v_t$$

Here, the variance of u at time t is determined by the square residual, which the primary regression model can quantify. 'P' delays are included in a second regression model, though. The equation represents the ARCH model with an order of p. The existence of the ARCH effect is assessed by evaluating the soundness of the null hypothesis.

$$H_0 = \gamma_0 = \gamma_1 = \gamma_2 = \gamma_p = 0$$

Generalized Autoregressive Conditional Heteroskedastic (GARCH) models

The Generalised ARCH model is a more expansive version of the ARCH model. The Generalised Autoregressive Conditional Heteroskedastic (GARCH) models were separately developed by Bollerslev (1986). These models allow for the conditional variance to be influenced by past own logs. The utilisation of the GARCH model has emerged as the conventional approach for modelling volatility in financial time series data. The mean equation of a GARCH (1, 1) model:

$$R_t = c + \beta R_{t-1} + \varepsilon_t$$

And the variance equation is:

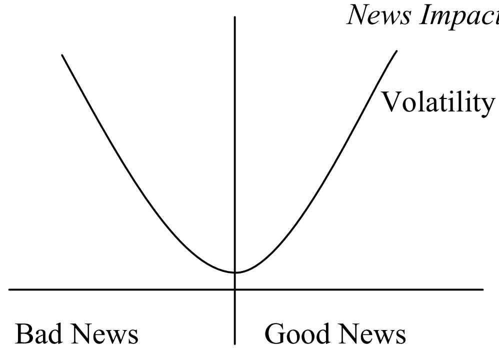
$$\sigma_t^2 = \omega + \alpha \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2$$

Where ω is constant, ε_{t-1}^2 is the ARCH term and σ_{t-1}^2 is the GARCH term. α reflects the impact of recent news (shocks) and β reflects the impact of old news (persistence volatility).The sum of the ARCH and the GARCH coefficients ($\alpha + \beta$) is very close to one or < 1 indicating that volatility shocks are quite persistent.

Asymmetry and leverage effects

Although ARCH and GARCH models are responsive to positive and negative news and are valuable for predicting and simulating volatility, they do not adequately capture the leverage impact and information asymmetry. The leverage effect is based on the rationale that the distribution of stock returns exhibits a high degree of asymmetry. The negative news is accompanied by a more significant surge in price volatility compared to the positive news, which yields equivalent rewards. Moreover, significant negative innovations result in greater volatility compared to lesser ones. Regardless matter the significance of happy news, its influence appears to remain consistent. The phenomenon of a disproportionate influence of news is referred to as the leverage effect. To elucidate the asymmetry of volatility in speculative prices According to Black (1976), when stock prices decrease, the value of the company's equity also decreases.

News Impact Curve



Various models have been suggested to reflect the asymmetrical nature of how volatility responds to changes in stocks. The two predominant GARCH formulations utilised to capture this imbalance are the exponential GARCH (EGARCH) model proposed by Nelson (1991) and the threshold GARCH (TGARCH) models developed by Zakoian (1994).

EGARCH models

Nelson (1991) discovered the Exponential GARCH (EGARCH) model. The model relies on a logarithmic function that represents the conditional variance. One can evaluate the Leverage effect to identify the optimal model that accurately represents the symmetries of the Indian Stock Market. To evaluate the EGARCH (1,1) model, we use the following equation:

$$In(\sigma^2) = \omega + \beta_1 In(\sigma_{t-1}^2) + \left\{ \left| \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \right| - \sqrt{\frac{\pi}{2}} \right\} - \gamma \frac{\varepsilon_{t-1}}{\sigma_{t-1}}$$

β represents the GARCH term, which accounts for the influence of the previous period's predicted variance. The left-hand side represents the lag of the conditional variance. The coefficient γ is sometimes referred to as the asymmetry or leverage term. The hypothesis that γ is less than zero will be used to test for the presence of leverage effects. The impact is symmetrical when γ is not equal to zero.

Threshold GARCH (TGARCH) Models

The Threshold GARCH (TGARCH) model was introduced by Zakoian in 1994. This is an alternative volatility model that permits asymmetric effects. The TGARCH model is widely regarded as the most appropriate method for assessing the effects of both positive and negative shocks on volatility. Engle and Ng (1993) found that negative shocks result in more volatility compared to positive shocks of equal magnitude. The TGARCH (1, 1) model is represented by an equation used to model the conditional variance:

$$\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \gamma d_{t-1} \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2$$

Where $d_{t-1} = 1$ if $\varepsilon_{t-1} < 0$ and $d_{t-1} = 0$ otherwise. In this approach, γ is referred to as the asymmetry or leverage effect. In this model, the positive news (εt-1 < 0) and the negative news (εt-1 < 0) have distinct impacts on the conditional variance. In this model, α represents the ARCH term and β represents the GARCH term. Therefore, if γ is both significant and positive, negative shocks will have a greater impact on than positive shocks.

V. Result & Analysis

GRAPHICAL PRESENTATION OF VOLATILITY CLUSTERING

The figures depict the daily returns of the (BSE and NSE) indices from April 2019 to March 2022. The graph offers valuable understanding of the significant instability observed in the present timeframe. The volatility clustering is examined by plotting the daily returns of the BSE and NSE indices. Figures 1 and 2 demonstrate that the daily returns of both the BSE and NSE indices.

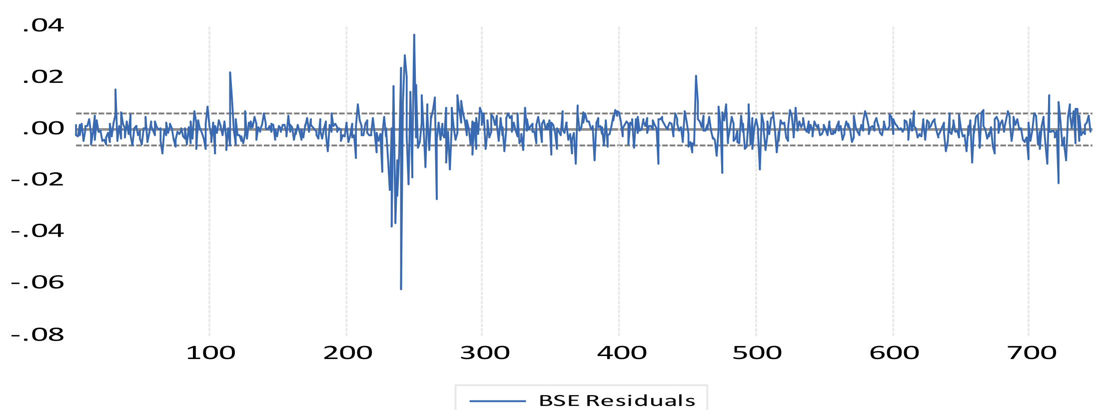


Figure 1: BSE

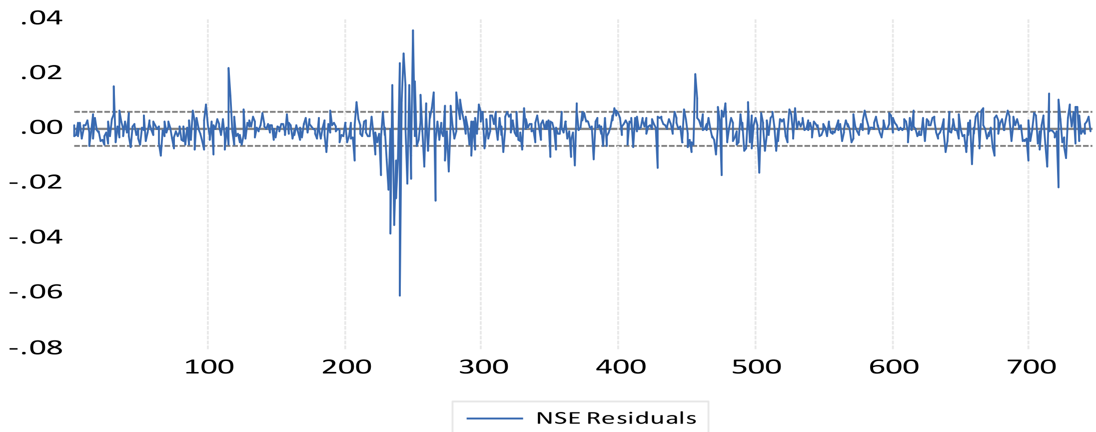


Figure 2: NSE

Table 1 demonstrates a significant variation in the daily returns of both indices. The average return and level of risk associated with the BSE index exceed those of the NSE. The NSE indexes exhibit negative skewness, indicating a longer left tail in comparison to the right tail. The indices exhibit a kurtosis value below 3, indicating the presence of heavy tails in their distribution. Additionally, the returns series of the indices demonstrate leptokurtic characteristics. In addition, the JB test statistics for the returns distribution of both indices are extremely high, and the probabilities of obtaining such statistics assuming normality are significantly close to zero (at the 99% confidence level). This confirms the rejection of the null hypothesis (H0: Normally distributed).

Table 1: Descriptive statistics

Index	OB	Mean	Median	Max	Min	Std. Dev	Skew	Kurt	JB	P-Value
BSE	744	4.6459	4.6161	4.7907	4.4146	0.0860	0.0053	2.0334	28.9669	0.0000
NSE	744	4.1179	4.0848	4.2666	3.8813	0.0879	-0.0010	2.0573	27.5488	0.0000

Detection of Arch Effect

In order to analyse the presence of the ARCH effect in the returns series of both indices, we first estimate an AR (1) model. Then, we calculate the squared residuals to conduct the ARCH-LM test. Table 2 show that the F-statistics and LM statistics (0.3155, 0.3162 and 0.2198, 0.2204, respectively) for the BSE and NSE indexes are statistically significant, indicating the presence of an ARCH effect in the returns. Ultimately, this outcome is validated by the Q-statistics, which is significant in all instances, indicating the presence of ARCH effect and leading to the estimation of GARCH effect.

Table 2: ARCH-LM test for ARCH effect of the BSE and NSE

Heteroskedasticity Test: ARCH						
BSE				NSE		
F-statistic	0.3155	Prob. *F*(1,740)	0.5744	0.2198	Prob. F(1,740)	0.6393
Obs**R*-squared	0.3162	Prob. Chi-square(1)	0.5738	0.2204	Prob. Chi-Square(1)	0.6387

The positive and statistically significant parameter β, as shown in Tables 3 and 4, provides clear evidence of the presence of the GARCH effect in the stock market. The Bombay Stock Exchange (BSE) and National Stock Exchange (NSE). The fluctuations in the Indian stock market, such as BSE and NSE, are found to be influenced by the introduction of fresh information. The equation for conditional variance involves the coefficients α and β, which represent the impact of new information. The coefficient α is statistically significant, suggesting that the current news has a considerable impact on the volatility of the stock market. Similarly, the β coefficient is statistically significant and indicates that the stock market volatility is being influenced by past news. Therefore, the null hypothesis is refuted, and the alternative hypothesis is validated. Given the statistical significance of the α and β coefficients, it is possible to make predictions about future stock prices.

Table 3: Estimation of GARCH (1, 1) model for BSE

GARCH = C(3) + C(4)*RESID(-1)^2 + C(5)*GARCH(-1)			
Variable	**Coefficient**	***z*-Statistic**	**Prob.**
C	8.81E-07	3.447451	0.0006
RESID(-1)^2	0.136745	6.956433	0.0000
GARCH(-1)	0.840944	36.71556	0.0000

Table 4: Estimation of GARCH (1, 1) model for NSE

GARCH = C(3) + C(4)*RESID(-1)^2 + C(5)*GARCH(-1)			
Variable	**Coefficient**	***z*-Statistic**	**Prob.**
C	9.24E-07	3.567485	0.0004
RESID(-1)^2	0.134736	6.830918	0.0000
GARCH(-1)	0.840012	35.67140	0.0000

The EGARCH model is employed to examine the leverage effect. Tables 5 and 6 demonstrate the presence of the leverage effect. Tables 5 and 6 demonstrate a statistically significant asymmetric impact (γ) of news in the test, with both α and β being significant. Therefore, both outdated news and the most recent news are influencing the stock market. Positive news stimulates an upward trend in stock prices, whereas negative news triggers a decline in stock prices. The coefficient γ is positive, greater than 0, and statistically significant at the 1% level. The data indicates that stock prices rise as a result of positive news entering the market, and this has a mitigating effect on market volatility.

Table 5: Estimation of EGARCH (1, 1) Model for BSE

LOG(GARCH) = C(3) + C(4)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(5) *RESID (-1)/@SQRT(GARCH(-1)) + C(6)*LOG(GARCH(-1))			
Variable	**Coefficient**	***z*-Statistic**	**Prob.**
C(3)	-0.426816	-5.994453	0.0000
C(4)	0.143300	4.293549	0.0000
C(5)	-0.141955	-9.802049	0.0000
C(6)	0.970179	174.3278	0.0000

Table 6: Estimation of EGARCH (1, 1) model for NSE.

LOG(GARCH) = C(3) + C(4)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(5) *RESID(-1)/@SQRT(GARCH(-1)) + C(6)*LOG(GARCH(-1))			
Variable	**Coefficient**	***z*-Statistic**	**Prob.**
C(3)	-0.432721	-6.193952	0.0000
C(4)	0.142174	4.464572	0.0000

C(5)	-0.135417	-9.912573	0.0000
C(6)	0.969380	176.8200	0.0000

A different approach to examine the uneven volatility in the BSE and NSE returns is the TGARCH model. Table 7 and 8 present the predicted outcomes of the TGARCH (1,1) model. The coefficient of leverage effect (γ) is shown to be positively and significantly associated with a 1% level of significance. This indicates that negative shocks or unfavourable news have a larger impact on the variance compared to good news or positive shocks. Similarly, the β coefficient is statistically significant and indicates that the volatility of the stock market is also being influenced by previous news. The coefficient γ is positive and bigger than 0, indicating that the impact is asymmetric. Any negative news in the stock market triggers greater volatility than positive news.

Table 7: Estimation of TGARCH (1, 1) model for BSE.

GARCH = C(3) + C(4)*RESID(-1)^2 + C(5)*RESID(-1) ^2*(RESID(-1)<0) + C(6)*GARCH(-1)			
Variable	**Coefficient**	***z*-Statistic**	**Prob.**
C	7.71E-07	5.050585	0.0000
RESID(-1)^2	-0.021316	-2.006811	0.0448
RESID(-1)^2*(RESID(1-)<0)	0.209624	7.981695	0.0000
GARCH(-1)	0.885114	62.42086	0.0000

Table 8: Estimation of TGARCH (1, 1) model for NSE

GARCH = C(3) + C(4)*RESID(-1)^2 + C(5)*RESID(-1) ^2*(RESID(-1)<0) + C(6)*GARCH(-1)			
Variable	**Coefficient**	***z*-Statistic**	**Prob.**
C	8.02E-07	5.314656	0.0000
RESID(-1)^2	-0.019146	-1.871276	0.0613
RESID(-1)^2*(RESID(-1)<0)	0.201978	7.800396	0.0000
GARCH(-1)	0.883966	61.82256	0.0000

The forecast error statistics for each model are contingent upon their capacity to anticipate future returns. Various methodologies are employed to assess and choose the most effective forecasting model. The root mean squared error (RMSE) is the predominant metric used. Additionally, there are less widely used metrics such as mean absolute error (MAE), mean absolute percent error (MAPE), and Theil inequality coefficient (TIC). Table 9 reveals that the EGARCH measure BSE index, when used for dynamic forecasting, yields the lowest values for RMSE, MAPE, and TIC. Therefore, the EGARCH measure is the most effective model for anticipating volatility in the BSE market. However, the NSE TGARCH metric is considered the most superior in this scenario. Both indices employ distinct methodologies to predict future volatility and return. However, when employing TIC, the EGARCH measure demonstrates superior performance for both types of indices, as it yields the lowest TIC value. However, the TIC metric is not widely used, thus we do not take it into consideration in this context.

Table 9: Comparison of (out-of sample) dynamic forecast performance measure

Index	Model	RMSE	MAE	MAPE	TIC
BSE	GARCH	0.102939	0.089438	1.933736	0.010971
	EGARCH	**0.062210**	0.045514	**0.988229**	**0.006680**
	TGARCH	0.064765	**0.045413**	0.989677	0.006946
NSE	GARCH	0.097919	0.082870	2.028167	0.011769
	EGARCH	**0.068046**	0.054337	1.319927	**0.008264**
	TGARCH	0.069753	**0.051344**	**1.262427**	0.008438

VI. Conclusion & Recommendations

The Indian economy had significant challenges during the Covid-19 pandemic. The lockdown scenario in the country has resulted in decreased profitability and productivity for businesses, leading to financial implications for the Indian stock market, including the Bombay Stock Exchange (BSE) and the National Stock Exchange (NSE). This study investigates the predicting of stock market volatility in India during the times of the COVID-19 pandemic. Indices exhibit volatility shocks. The GARCH coefficient indicates that the current returns of the indices tracked by the EGARCH measure are influenced by historical volatility. Based on the EGARCH measure, the indices' returns are unaffected by the leverage effect, indicating that positive changes are less impactful than negative changes. Conversely, the TGARCH measure shows that negative news leads to higher conditional volatilities. Asymmetric shocks are evident in the returns of the BSE indices, and these shocks endure for an extended duration. The TGARCH measure demonstrates the presence of the leverage impact in the indices. Based on the conditional volatility graph, the volatility shocks exhibit a significant level of persistence between 2019 and 2022, followed by a period of relative stability. Ultimately, the TARCH method stands out as the most effective forecasting measure for the Indian Stock Market. Conversely, the EGARCH metric is most suitable for analysing the NSE index. Therefore, it is advisable to consider alternative methodologies for volatility modelling, apart from GARCH, EGARCH, and TGARCH, in order to obtain varied outcomes. The current study centred on predicting the level of volatility in the Indian stock market. The study suggested that academics should do a comparative analysis of the volatility of the Indian stock market in relation to other stock exchanges in emerging countries.

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