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Asymmetric Effects and Volatility Clustering in NSE NIFTY 50: A Comparative Analysis of GARCH Models

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Authors' contributions

This work was carried out in collaboration between both authors. Author RRM is responsible for the conceptualization and design of the study. Author RRM conducted the statistical and econometrical analysis using various GARCH models and write the paper. Author RRM review the results, supervise modifications and make important contributions to the final version. Both authors read and approved the final manuscript.

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ABSTRACT

This study aims to analyze the volatility patterns, Clustering, and asymmetric effects in the NSE NIFTY 50 index. It involves using daily returns data from the NSE NIFTY 50 from 01 Jan 2010 to 31 Dec 2023. Daily closing prices are obtained from the official NSE website, and returns are calculated based on these prices. EGARCH (1, 1), TARCH (1, 1), GARCH (1, 1), GARCH-M (1,1), and models are utilized to predict volatility, capturing volatility clustering and leverage effects. Using both the Akaike and Schwarz criteria, EGARCH (1,1) was demonstrated to be the best model. The findings reveal that Fluctuations in the Indian stock market, particularly shown in the NIFTY index of

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the NSE were the highest in the year 2020 due to the COVID-19 pandemic. Past NIFTY returns demonstrate a GARCH effect on today's NIFTY returns. The results of the research suggest that the impact of negative and positive shocks on the stock returns series varies. Volatility is largely caused by negative news compared to positive news. It is suggested that the model exhibits a leverage effect and that different types of information produce various types of shock to the volatility of the Nifty index return. The findings show that investors of NSE, particularly those involved with the NIFTY50, face heightened volatility and increased risk, especially during periods of significant events.

Keywords: Stock market; volatility pattern; nifty 50; volatility clustering; asymmetric effects.

1. INTRODUCTION

The degree to which the price of a financial instrument or market index fluctuates over a specific time is referred to as market volatility. It gauges the degree to which the price of an asset deviates from its predicted value, which impacts a range of financial instruments including bonds, currencies, and stocks (Dixit & Agrawal, 2019). Stock values are influenced by economic factors such as GDP growth, inflation, employment, and interest rates; good indications cause prices to rise, while negative indicators cause them to fall. Stock prices are impacted by company performance, including revenue growth and EPS (Bekaert & Wu, 2000). Geopolitics-related events, such as trade disputes and conflicts, may affect investor behaviors and produce market volatility. Not every change in a company's stock price indicates a problem with its fundamentals (Gupta, 2024). A few are typical characteristics of the market. Investors may determine a company's worth with the use of fundamental research, preventing rash decisions in response to transient fluctuations (Gabriel, 2012). Governments may reduce volatility in the stock market by putting in place measures that improve market stability, bolster investor confidence, and stimulate the economy. Volatility can be decreased by implementing regulatory changes that enhance market integrity, transparency, and investor protection (Habiba et al., 2019). The standard deviation of Stock returns during a specific time frame serves as an indicator of volatility. It is a measure of how much a stock fluctuates over some time. Beta Measures the Market risk or systematic risk of portfolio but Volatility measures the total risk. The beta is a measure of the correlation between the market and the stock (Kumar & Gupta, 2009). The presence of volatility negatively affects investors' decisions regarding the efficient arrangement of resources. And, consequently, their options for stock market investments (Dwarika, 2022). Rising volatility inspires shareholders to be cautious about holding various stocks due to the heightened uncertainty in the market. As a result, investors demand higher risk premiums to compensate for the risk resulting from market volatility (Bashir et al., 2015). Investing in the stock market is commonly perceived as risky due to its inherent volatility. The stock market is volatile because macroeconomic factors have an impact on it and have an impact on stock prices. These elements may be particular to a company and may affect a single firm's price. Investors interpret heightened volatility as an indication of a trader's anxiety, whereas minimal volatility is perceived as an indication of investor assurance (Jain & Dash, 2012). **"**Investments in the stock market might be highly turbulent, but they also contribute to the expansion and robustness of the economy. The exchange of securities and transactions involving securities is facilitated by the securities market" (Agarwal, 2020).

2. LITERATURE REVIEW

Fakhfekh et al. (2023) The GARCH model was used to better show the patterns of volatility in Tunisia's sectoral stock market during the COVID-19 epidemic. It has been observed that volatility continued longer after the COVID-19. The study found that the asymmetric influence of building construction materials, the construction business, and the food and beverage industries on return volatility was minimal. The banking sector, consumer service sector, basic materials, financials and distribution, and basic materials, on the other hand, all had significant positive asymmetric impacts on return volatility.

Ahmad et al. (2016) Their focus is based on the Volatility of the Stock Market along with macroeconomic factors. This research examines the Karachi Stock Market for fourteen years, with a particular emphasis on five macroeconomic issues. Macroeconomic factors influence the economy and each other. Equity markets are impacted by this. Models such as GARCH and

VAR examine their volatility and correlations. The study concludes that different macroeconomic factors have diverse effects on stock returns and indexes due to their unique behaviors and linkages. Stock movements are heavily impacted by variables like exports and inflation.

Bashir et al. (2015) Examine the influence of FII investments on stock market volatility. The study focuses on monthly time series of SENSEX, NIFTY, and FIIs activity over fifteen years. According to the study, the volatility of the Indian stock market is impacted by previous periods' volatility, and FII investment also has a major impact on the volatility of NIFTY and SENSEX. The volatility of FIIs and the Indian stock market rose with time, even though it reached its highest point during the financial crisis, it eventually reverted to its typical state.

Birău and Trivedi (2015) The work in this paper focuses on examining the historical volatility of the Indian Stock Exchange (NSE) using GARCH models along with asymmetric GARCH models, volatility clustering, international portfolio diversification, globalization, and financial integration. This study analyses the CNX 100 index volatility clustering experimentally using 1698 daily observations from October 2007 to July 2014. Based on analysis, the CNX 100 index demonstrated a typical pattern of market volatility from 2009 until the start of 2013. Due to positive skewness, a high degree of kurtosis, and consideration of lower standard deviations, investors' earnings have been maximized. Investors may find the National Stock Exchange (NSE) index CNX100 to be a better option as It permits the coalition of 38 economic sectors while maintaining the unrestricted movement of capital within a range of 75% to 82%.

Bhatia et al. (2014) Aim to explore the essence of the volatility of the China and India markets and investigate the association among them. The transmission of volatility between the two countries is analyzed Using the test of Granger causality. The results indicate that both India and China experienced their highest levels of volatility in 2008. The Indian market is observed to exhibit greater volatility compared to the Chinese stock market. A unidirectional causal relationship between the Chinese and Indian markets may be found.

Ali (2016) This research emphasizes the association between stock returns and volatility, as well as the clustering of volatility, leverage Effect, and persistence of volatility along with the GARCH and EGARCH model for the Indian stock markets, specifically NSE and BSE from 2006 to 2014. The correlation between returns and volatility, as well as the clustering and persistence of volatility, are all examined using the GARCH model. The EGARCH model encapsulates the impact of asymmetry. Recent and past news significantly impact volatility, with a notable leverage effect: negative shocks wield greater influence.

Agarwal (2020) This study looks at stock market volatility in the Indian stock markets using the GARCH model. over the years 2015–20. The findings show that both exchanges' volatility clusters, with BSE indices showing higher volatility than NSE, suggest a higher level of risk for investors. Both the market indices are volatile; descriptive statistics show that Compared to NSE indices, BSE and sectoral indices exhibit higher levels of volatility. The statistics clearly show persistent rising and negative tendencies as volatility clustering. The persistent downward trend that began in late January 2020 points to a possible upsurge.

Khan and Zia (2019) The research investigated how the announcement of mergers involving SBI and its affiliated banks influenced the volatility of SBI stock returns over 300 days. The study utilized the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model, renowned for analyzing time series data, to elucidate the volatility in return patterns. The findings suggested that merger announcements were anticipated to prompt a response in returns, potentially leading to greater abnormal returns for investors within a shorter timeframe.

Le and Tran (2021) examined the possibility of financial spread during the COVID-19 and worldwide financial crises from the American stock market to the stock markets in Vietnam and the Philippines. This influence was noted for the Vietnamese stock market, but no indication of any potential During the global financial crisis, there was discovered to be a contagion from the U.S. stock market to the Philippine stock market. The stock markets in Vietnam and the Philippines, two of these emerging nations, were also impacted by the COVID-19 transmission impact. Conversely, the Philippines had the opposite experience of a contagion effect crisis during the coronavirus epidemic while Vietnam witnessed less of one than it did during the global financial crisis.

3. OBJECTIVES

1. To examine the volatility pattern of NIFTY 50 of the Indian stock market.
2. To estimate the existence of Leverage effect and volatility Clustering.
3. To know the best-suited model to measure volatility.

4. METHODOLOGY

This study employs both descriptive and analytical techniques. The distributional characteristics of the daily return series are determined in this research by calculating descriptive properties such as Mean, Median, Standard Deviation, Kurtosis, and Skewness. The target group of the study is restricted only to the market indices NSE NIFTY 50. The present study covers the last 14 years data from January 01, 2010, to December 31, 2023. According to Engle and Mezrich (1995), proper GARCH estimation requires at least 8 years of data. The sample size consists of 3471 observations of the indexes' closing prices each day to analyze the ups-down of the stock price in the Indian market. Secondary data for the research was gathered from the official NSE website, accessible at www.nseindia.com.The daily ending value of NSE NIFTY 50 is considered for the study. Volatility is estimated on daily index returns (Pushpalatha et al., 2019). Daily return will be calculated by using the following formula: -

$$R_t = \log (P_t / P_{t-1}) * 100 \qquad (1)$$

Where Pt is the stock price on day t, Rt is the daily return on stock, and Pt-1 is the stock price on day t-1. The TARCH (1, 1), EGARCH (1, 1) GARCH (1,1), GARCH-M (1,1) and Philips-Perron (PP) tests, as well as the Augmented Dickey-Fuller (ADF), Jarque–Bera (J-B) test and Autoregressive Conditional Heteroscedasticity - Lagrange Multiplier (ARCH-LM) tests, were utilized to check the existence of leverage effects in volatility (Trivedi et al., 2020). The analysis was made using E-views 10 software. The GARCH model (Bollerslev, 1986) applies to the whole financial time series and permits the conditional variance to be based on prior lags. On the other hand, the mean equation yields the initial lag of the squared residual, it gives an idea of the volatility from earlier times. The most popular model of GARCH (1, 1) has as its basis the following mathematical statement:

$$h_t = \omega + \alpha_1 u^2_{t-1} + \beta_1 h_{t-1} \qquad (2)$$

To support the unconditional variance theory based on stable covariance, the following expressions have to be established by the empirical analysis:

$$\sigma^2 = \mathrm{Var}(u_t^2) = E\,(\omega + \alpha_1 u^2_{t-1} + \beta_1 h_{t-1}) \qquad (3)$$

$$\sigma^2 = \omega + \alpha_1 E(u^2_{t-1}) + \beta 1 E(ht_{-1}) = \omega + \alpha_1 \sigma^2 + \beta 1 \sigma^2 \ (4)$$

Considering applying the equation for the conditional variance in the GARCH (1, 1) model $\mathrm{Var}(u_t/ht_{-1}) = E(u^2_t/h_{t-1}) = h_t$, it may be expressed as follows: i.e.: $h_t = \omega + \alpha_1 u^2_{t-1} + \beta_1 h_{t-1}$. The final formulation is $h_t = \omega + \alpha_1 u^2_{t-1} + \beta_1 h_{t-1}$. It depends on both GARCH and ARCH terminology (Meher et al., 2023). The ARCH component is represented by $\alpha_1 u^2_{t-1}$, while the GARCH component is represented by $\beta_1 h_{t-1}$.

This is the econometric framework that forms the basis of the model specifications. If the unconditional variance is found, the scenario necessitates the use of the financial modeling procedure, which essentially entails computing the arithmetic expression that follows:

$$\alpha_1 + \beta_1 < 1$$

To transform it into a positive outcome, the condition $\alpha_0 > 0$ needs to be validated. Good news for the market will be shown by positive outcomes. Our formula for the constant, conditional mean was as follows: $E(y_t/O_{t-1})$ where y_{t-1} is included in $|\ O_{t-1}|$ and $E = c + \phi y_{t-1} + o$. The ultimate empirical result utilizing $h_t = \omega + \alpha_1 u^2_{t-1} + \beta_1 h_{t-1}$ will be made easier by the preceding frame (Mishra et al., 2022).

5. RESULTS AND DISCUSSION

The NIFTY 50 index returns for the research period are descriptively analyzed in Fig. 1. A 0.000410 mean and a 0.010665 standard deviation are displayed in the table. A growth in the share price throughout that period is indicated by the positive returns mean. A higher likelihood of producing returns that exceed the mean is shown by the distributions' negative skewness. NIFTY index returns exhibit non-normal distributional kurtosis and are leptokurtic (> 3), indicating that the data is fat-tailed (Bora & Adhikary, 2021). Further evidence that it is meaningful at the 1% level comes from the Jarque-Bera test. Normality is thus rejected as the null hypothesis.

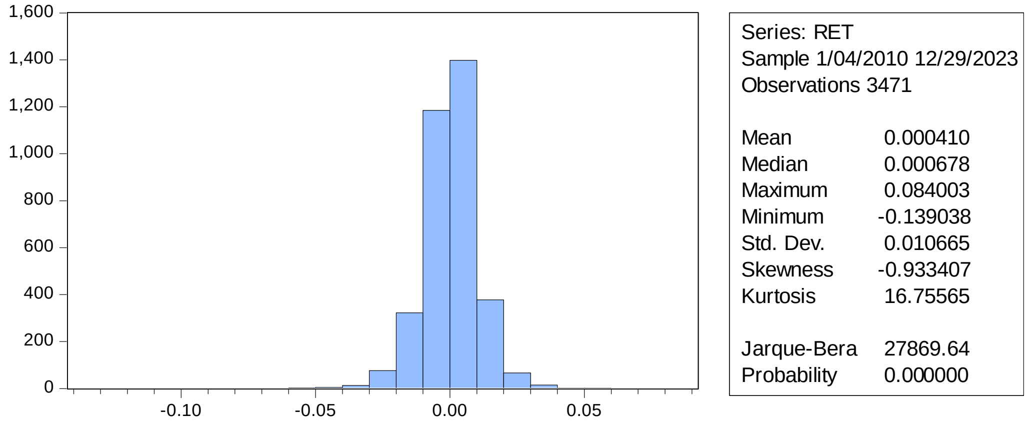

Fig. 1. Descriptive statistics
Source(s): Authors' EViews 10 Calculation

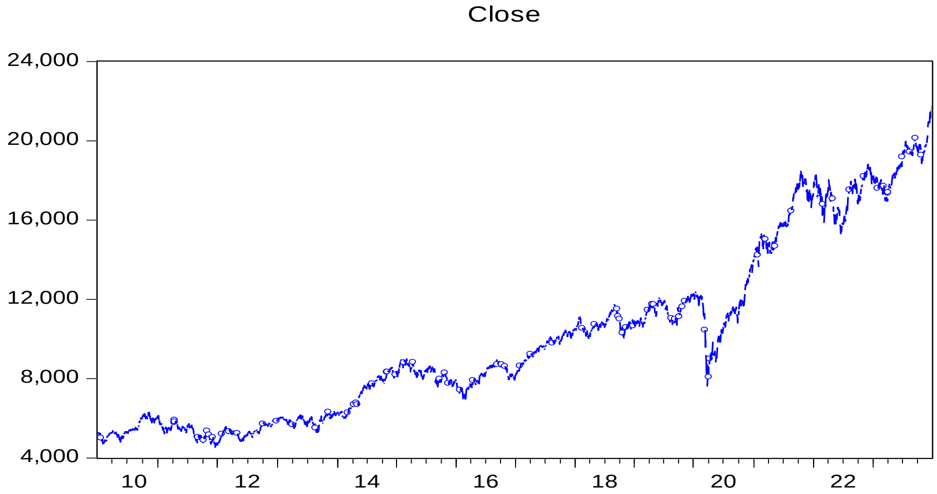

Fig. 2. The trend of NIFTY 50 index (individual chart)
Source(s): Authors' EViews 10 Calculation

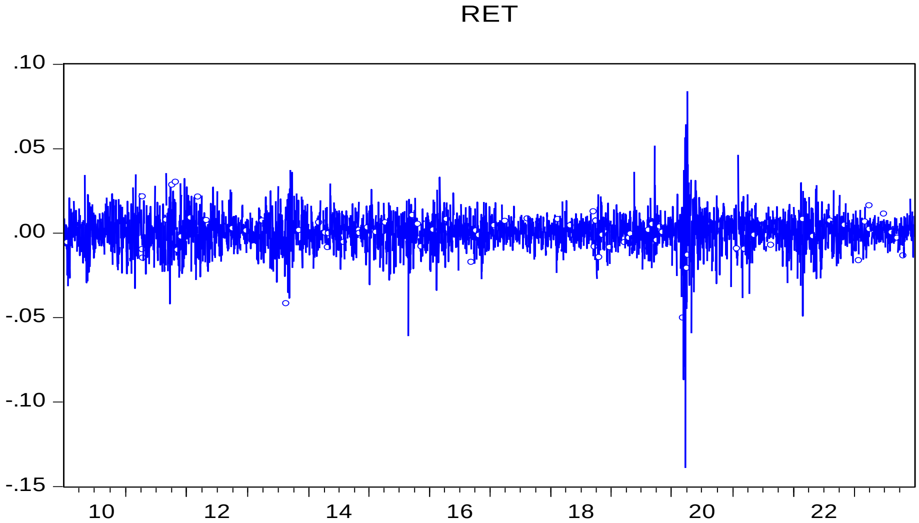

Fig. 3. Log returns series of NIFTY 50
Source(s): Authors' EViews 10 Calculation

Table 1. Unit root test

Value	ADF	PP
T-Statistic	-58.06941	-58.08962
Prob**.**	0.0001	0.0001
Critical Value		
1%	-3.432047	-3.432047
5%	-2.862175	-2.862175
10%	-2.567152	-2.567152

Source(s): Authors' EViews 10 Calculation

Table 2. ARCH test

Heteroskedasticity Test: ARCH LM			
F-statistic	1.243575	Prob. F (1,3462)	0.2649
Obs*R-squared	1.243846	Prob. Chi-Square (1)	0.2647

Source(s): Authors' EViews 10 Calculation

Table 3. Estimated result of GARCH (1, 1) model

GARCH = C (4) + C (5) *RESID (-1) ^2 + C (6) *GARCH (-1)				
Variance	**Coefficient**	**Std. Error**	**z-Statistic**	**Prob.**
Mean Equation				
C	0.000726	0.000139	5.231936	0.0000
Variance Equation				
C	1.89E-06	3.93E-07	4.807060	0.0000
RESID (-1) ^2 (α)	0.084527	0.006842	12.35459	0.0000
GARCH (-1) (β)	0.898941	0.009096	98.83299	0.0000
α + β	0.983468			
Durbin-Watson stat	**Akaike info. Criterion**		**Schwarz Criterion**	
1.960497	-6.503902		-6.493252	

Source(s): Authors' EViews 10 Calculation

The series returns (see Fig. 2) provide an apparent indication of the market decline caused by the global financial crisis. The scale following the financial crisis and the ratios indicating positive returns should be the main areas of interest for investors, scholars, and researchers (Jindal & Gupta, 2022). It demonstrates unambiguously how highly investors view investments in the long run. However, a lengthy succession of normal volatility rates and quantifiable unusual scales are present in the NIFTY 50 index. The 50 distinct economic sectors included in the NSE NIFTY index return series offer substantial growth support for the financial series.

The volatility clustering of the NSE NIFTY return from January 2010 to December 2023 is shown in Fig. 3. It is noted that periods of low volatility tend to persist, followed by extended durations of low volatility, while periods of increased volatility tend to be succeeded by prolonged periods of elevated volatility (Lobão, 2023). This illustrates that the NIFTY 50 index return series fluctuates around a consistent mean, yet the variance changes over time, exhibiting clustered volatility. The existence of the presence of a unit root in the series, as assessed by both the ADF and PP tests detailed in Table 1, is contradicted at the 1% significance level. The test statistics in Table 1 surpass the critical value of –3.43 for detecting a unit root in the return series. Furthermore, the p-values for both PP and ADF are below 0.05. Consequently, the results from both tests affirm the stationary characteristics of the series.

Table 2 displays the predicted ARCH-LM test result. The ARCH-LM test checks for heteroskedasticity and is applied to the GARCH model-estimated residual. The outcomes of the ARCH-LM test show that there is no heteroscedasticity in the residuals obtained from the regression estimation ($P > 0.05$). As a result, there is no residual ARCH influence in the ARCH-LM outcome (Singh & Tripathi, 2016).

Table 3 indicates the GARCH (1, 1) model's estimated result. The constant value of the average equation is positively and significantly associated at a significance level of ($P < 0.05$). The parameters for each RESID (-1) ^2 and

GARCH (-1) are found to be significant. The total of these terms (α and β) is 0.983468, which is quite near to 1 and indicates that volatility occurs frequently in nature. As a result, the GARCH model demonstrated that the Indian stock market exhibits constant conditional variation. The Akaike and Schwarz values of the model are -6.503902 and -6.493252 respectively. The DW statistics value is 1.960497**,** which is near 2**.** It indicates there is no autocorrelation between the error terms, showing that the statistical model is suitable and fit. Based on the conclusive statement for the GARCH (1, 1) model regarding the data series of the NIFTY 50 index is as follows.

$\sigma^2_t = \alpha_0 + \alpha_1\mu^2_{t-1} + \beta_1\sigma^2_{t-1}$ and outcomes (α1) +(β1) = 0.084527 + 0.898941 = 0.983468 < 1

The GARCH (1, 1) model fits the estimated movement of the NIFTY 50 (National Stock Exchange index) exactly, providing a value of 0.983468, which is less than or extremely near to 1. It suggests that series have a significant influence on listed equities and a considerable amount of volatility. Both the ARCH term and GARCH term serve as the basis for the GARCH (1,1) model formulations. The findings suggest Investing for a long period in any NSE index company will provide profits (Srihari et al., 2024).

The GARCH-M (1, 1) model's projected result can be seen in Table 4. Conditional Variance i.e. GARCH is captured in the mean equation. The GARCH-M model incorporates a heteroskedasticity factor into the mean equation to explain situations where a security's return is contingent on its volatility, or risk. Serial correlations in the return series are implied by the GARCH-M model formulation (Bhowmik & Wang, 2020). The mean equation's GARCH term is not significant but by including it in the mean equation it has improved significance in the variance equation. If you want to hedge against risk, the risk premium is not very high. It means that taking risks does not give you more returns (Mishra & Mishra, 2024).

Table 4. Estimated result of GARCH-M (1, 1) model

GARCH = C (5) + C (6) *RESID (-1) ^2 + C (7) *GARCH (-1)				
Variance	**Coefficient**	**Std. Error**	**z-Statistic**	**Prob.**
Mean Equation				
C	0.000470	0.000254	1.849987	0.0643
GARCH (risk premium)	3.340914	2.808869	1.189416	0.2343
Variance Equation				
C	1.91E-06	3.98E-07	4.797624	0.0000
RESID (-1) ^2 (α)	0.085017	0.006903	12.31637	0.0000
GARCH (-1) (β)	0.898294	0.009154	98.13569	0.0000
α + β	0.983311			
Durbin-Watson stat	**Akaike info. Criterion**		**Schwarz Criterion**	
1.951245	-6.503865		-6.499428	

Source(s): Authors' EViews 10 Calculation

Table 5. Estimated result of EGARCH model

LOG(GARCH)=C (4) + C (5) *ABS (RESID (-1)/@SQRT (GARCH (-1))) + C (6) *RESID (-1)/@SQRT (GARCH (-1)) +C (7) *LOG (GARCH (-1))				
Variance	**Coefficient**	**Std. Error**	**z-Statistic**	**Prob.**
Mean Equation				
C	0.000411	0.000129	3.192458	0.0014
Variance Equation				
C (4)	-0.362155	0.036167	-10.01341	0.0000
C (5)	0.130477	0.013469	9.6687330	0.0000
C (6)	-0.098517	0.006530	-15.08776	0.0000
C (7)	0.972086	0.003339	291.1722	0.0000
Durbin-Watson stat	**Akaike info. Criterion**		**Schwarz Criterion**	
1.971715	-6.538799		-6.534363	

Source(s): Authors' EViews 10 Calculation

Table 6. Estimated result of TGARCH model

GARCH = C (4) + C (5) *RESID (-1) Λ2 + C (6)) *RESID (-1) Λ2*(RESID (-1) <0) + C (7) *GARCH (-1)				
Variance	**Coefficient**	**Std. Error**	**z-Statistic**	**Prob.**
Mean Equation				
C	0.000474	0.000141	3.363321	0.0008
Variance Equation				
C	2.81E-06	3.67E-07	7.654150	0.0000
RESID (-1) ^2 (α)	0.003185	0.006873	0.463321	0.6431
RESID (-1) Λ2*(RESID (-1) <0) (Y)	0.139456	0.011335	12.30359	0.0000
GARCH (-1) (β)	0.896471	0.008550	104.8495	0.0000
Durbin-Watson stat	**Akaike info. Criterion**		**Schwarz Criterion**	
1.965668	-6.534723		-6.522298	

Source(s): Authors' EViews 10 Calculation

Table 7. Model selection criteria

Criteria	ARCH (A)	GARCH (B)	GARCH -M (C)	EGARCH (D)	TGARCH (E)	Best Model
Log likelihood	11003.17	11274.95	11274.95	11335.47	11328.41	D
Akaike	-6.348149	-6.503902	-6.503865	-6.538799	-6.534723	D
Schwarz	-6.339274	-6.493252	-6.491440	-6.526374	-6.522298	D
Hannan-Quinn	-6.344980	-6.499428	-6.499428	-6.534363	-6.530287	D

Source(s): Authors' EViews 10 Calculation

Table 5 displays the EGARCH (1, 1) model's result. The asymmetric term has a negative coefficient (-0.09851) and is at the 1% level statistically significant. The result indicates that the leverage effect is present (Guirguis, 2024). The statistically significant negative value -0.098517, in C (6) indicates that both good and negative information in the market has a mixed effect on price fluctuations. In the results C (6) ω < 0 (-0.098517) the Negative shocks tend to create greater volatility compared to positive shocks. Therefore, negative news contributes far more to volatility than positive news (Umar et al., 2021). The model's AIC and SC criteria are, respectively, -6.538799 and -6.534363.

The TARCH (1, 1) model is employed for measuring the leverage effect, and the results of the model are shown in Table 6. There are asymmetries in the news for this stock, as indicated by the positive coefficient of the asymmetric term (0.139456), This finding holds statistical significance at the 99% confidence level. The C (6) *(RESID (-1) ^2*(RESID (-1) <0) is positive i.e**.** 0.139456 and statistically significant. In this result, α + Y > α (0.003185 + 0.139456 > 0.003185) indicates that Negative information tends to have greater influence than positive news. This provides validity to the claims that the model has a leveraging effect and that the volatility of the Nifty index return is more affected by adverse information (Suleymanov et al., 2024). The model's Akaike and Schwarz criteria are -6.534723 and -6.522298, respectively. The TARCH model provided a more satisfactory explanation of Nifty's volatility.

6. CONCLUSION

The study finds out whether the returns of the nifty from the previous day could explain today's nifty 50 returns by employing a GARCH model. The findings reveal that the parameter is both statistically significant and positive, suggesting that past nifty returns exhibit a GARCH effect on today's nifty returns. The primary objective was to analyze the volatility of the NSE NIFTY 50 index in the stock exchange spanning from Jan. 2010 to Dec. 2023. Tests were conducted to verify the existence of leverage effects, unit roots, and volatility clustering, all of which were established conclusively (Lakshmi, 2013). The outcomes of the ARCH-LM test indicate that there is an absence of heteroscedasticity within the residuals obtained from the regression estimation (p>0.05). So, the result from ARCH-LM doesn't retain any additional residual impact from ARCH. In the GARCH, the constant value and mean equation are Statistically meaningful with a confidence level below 0.05. The parameters α and β added together are 0.983468, nearly equal to 1, indicating that volatility is highly repeated in nature. Therefore, conditional variance continues in the Indian stock exchange, as demonstrated by the GARCH model. At 1.960497**,** the Durbin-Watson statistics value is nearer to 2. It suggests that the statistical model is appropriate and fit because it indicates the error terms do not exhibit autocorrelation. The models TGARCH (1, 1), EGARCH (1, 1), GARCH (1, 1), and GARCH-M (1, 1) are used to evaluate the Nifty index returns. The findings showed that the coefficient may indicate something in both the positive and TARCH and the positive with a confidence level below 0.05 TARCH models. Also, it has been shown that the most effective model is EGARCH (1, 1) for eliminating asymmetric volatility (Bonga 2019, Jebari & Hakmaoui 2019). The statistical summary indicates a risk degree of 0.010665**,** with mean and median returns close to zero. Analysis of 14-year daily market data, comprising 3471 observations, reveals a negative skewness. Specifically, the presence of high kurtosis and negative skewness suggests a heightened likelihood of earning returns, though accompanied by a lower degree of standard deviations, thus offering the potential for higher returns on investments but also entailing some risks (Subburayan, 2023).

7. IMPLICATIONS

Due to the expected rapid economic development and rising foreign interest of investors with respect for the nation. It is important to analyze the trends in the volatility of the Indian stock market, characterized by persistence, time-variance, and predictability. This may help in portfolio diversification and to save from risk due to fluctuation in share price. Volatility forecasts are valuable for portfolio management and assessing performance. This research aims to aid investors in comprehending the future, past, and present conditions of the Indian stock market, enabling them to predict future trends based on historical data and make informed investment decisions. Only secondary data was used in the study, and the accuracy of the secondary data will determine how reliable the findings are. The Indian stock market has been represented by the NSE NIFTY 50. The idea of volatility can also be studied using other stock market indices. Daily data has been used for analysis. The data analysis might have also been done with monthly, quarterly, or annual data. The study is only being conducted for 14 years. The researcher can increase the period as per their convenience and availability of data.

DISCLAIMER (ARTIFICIAL INTELLIGENCE)

Author(s) hereby declares that NO generative AI technologies such as Large Language Models (ChatGPT, COPILOT, etc.) and text-to-image generators have been used during the writing or editing of this manuscript.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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