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VOLATILITY MODELING AND RISK ESTIMATION OF NIFTY 50 RETURNS ON THE INDIAN STOCK MARKET: AN APPLICATION OF GARCH MODELS

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Abstract

This study focuses on the application of GARCH models to examine the return volatilities and risk characteristics of the Nifty 50 index, a key benchmark in the Indian financial market. Derivatives, which derive their value from underlying assets such as the Nifty 50, have become increasingly popular due to their relatively low capital requirements and strategic benefits for investors and financial managers. In order to explain the return volatilities of Nifty 50 index, we first discovered that a heavy-tailed distribution must be incorporated into the GARCH models. Next, we examine the VaR estimates using the parametric approaches, specifically the GARCH model with the normal inverse Gaussian distribution (GARCH-NIG) and GARCH model with the normal distribution (GARCH-Normal). Our findings show that while the GARCH-Normal model's VaR estimates are the most effective, the GARCH-NIG model's VaR estimates are the best. We conclude that the GARCH-NIG model has the potential to produce precise VaR estimates for the return series of Nifty 50 index. Additionally, we discovered that, unlike Nifty 50 index, the return volatilities of Nifty 50 index do not rise higher in reaction to positive shocks than to negative ones. Overall, our findings suggest that the GARCH-NIG model offers a robust framework for risk estimation and volatility modeling of the Nifty 50 index, with significant implications for portfolio management and financial risk assessment in the Indian equity market.

Keywords: Nifty 50 index, GARCH models, Volatility, VaR Risk, Heavy-Tailed Distribution.

I. Introduction

The Indian government's numerous initiatives since 1991, the effects of "liberalisation," "privatisation," and "globalisation" policies, as well as ensuing financial sector reforms, have all contributed to the substantial shifts and structural changes in the Indian stock market [1]. Since the 1970s, when options trading first began, its effect on stock market volatility has undergone substantial modification. Numerous studies show that futures trading lowers spot market volatility by integrating advanced risk management systems, removing information asymmetry, increasing the amount of information available to the price formation process, improving price discovery efficiency, and increasing profits by minimising risk [2]. During periods of significant market volatility, like the global financial crisis of 2007–2009 and the 1987 U.S. stock market crash, this occurrence is most common. Furthermore, when derivatives are introduced to the Indian stock market, they create significant opportunities for hedging and speculating, which lead to price instability and amplify the underlying market volatility [3]. However, when compared to cash market assets, a vast number of investors and financial managers view derivatives as highly captive due to their low initial requirements with the clearing house for futures, the payment of premiums for options, and their low transaction costs [4-5]. Since there is no solid empirical evidence that the index option causes volatility to fluctuate, over the past few decades, scholars and industry professionals have been very interested in the economic impact of Nefty index derivatives on stock market volatility [6]. Regarding the effect of index derivatives on the volatility of the underlying market, this presents significant queries for investors, researchers, academics, and financial managers [7]. The majority of previous research has actually demonstrated that the introduction of index futures may result in a stabilisation or a reduction in volatility [5,8-10].Many financial decisions require evaluating volatility and examining the behaviour of the stock price [11-13]. To account for the time-varying variance, Engle developed the ARCH model, an autoregressive conditional heteroscedasticity model [14]. It has been regularly utilised in academic circles to examine stock price volatility ever then [15]. A variety of theories have been used to explain the volatility of stock prices. Stock price synchronisation is the main emphasis of the approximation factor model [16]. Price-type and quantity-type monetary policies' dynamic impacts on stock prices may be effectively studied using the MCMC approach, the TVP-SV-VAR model, and the Kinetic Ising Model [17-18]. The effect of diverse herd behaviour on stock price fluctuations may be simulated using an agent-based artificial market simulation platform [19]. In economics and finance, the GARCH family of models has been widely employed, especially for estimating volatility [20-24]. Heteroskedasticity and time-varying volatility are seldom taken into account by GARCH models [25-26]. we take into consideration the GARCH-Normal and GARCH-NIG frameworks in this study.To examine the effect of futures trading on market volatility in the Indian setting, a number of scholars used ARCH and GARCH models, including [5,27-30]. They discover that conditional volatility and derivative introductions are strongly correlated. Accordingly, the earlier news has a low impact whereas the later news has a strong impact. By using GARCH, [31-33] investigated the underlying market volatility. They found that the futures and options coefficient's magnitude is extremely small, indicating that futures and options derivatives have a negligible impact on volatility. By using symmetric GARCH approaches, [34-35] investigated the impact of futures trading starting in the Indian capital market between April 1997 and April 2007. The findings show no discernible change in volatility and are in line with those of the majority of earlier research. The [36] used GARCH to test the conditional volatility of the S&P CNX Nifty index and discovered a rise in the conditional volatility of the S&P CNX Nifty index after analysing the influence of derivatives on the underlying market over a period spanning from January 1991 to December 2011. The impact of option listing on small, mid, and large-cap companies varies, according to Joshi [37], and optioned equity volatility sharply increases for large-cap firms.This research's main goal is to examine the NSE NIFTY 50 Index's volatility behaviour using two different GARCH-type modelling techniques: the GARCH-Normal model and the GARCH-NIG (Normal Inverse Gaussian) model. Skewness, kurtosis, and heavy tails are empirical properties frequently seen in financial time series that are taken into account by the GARCH-NIG model, whereas the GARCH-Normal framework assumes properly distributed return innovations. In order to determine whether model more accurately depicts the features of volatility in the Indian equities market, the study will compare these two frameworks. The investigation will yield important information about the accuracy of risk forecasting, the persistence of volatility, and the suitability of distributional assumptions in modelling stock returns. The results are meant to improve risk management procedures and facilitate better decision-making for investors, financial analysts, and legislators who are interested in Indian market stability and investment tactics.The rest of our research is structured as follows: The GARCH models are described in Section 2. The data is then described and the estimation results are shown in Section 3. Section 4 provides a final summary and conclusion.

II. Methods

I. GARCH Models

The Nifty 50 index return, or y_t, is determined using the ARMA-GARCH models and is the natural logarithm of the ratio of two consecutive prices. To choose the model with the lowest Akaike Information Criterion (AIC), we use an automatic approach to choose the autoregressive-moving-average (ARMA) model for the mean equation process. Our findings show that, out of the three-return series, an AR (1) with no intercept term has the lowest AIC. One way to express the model is as

$$y_t = \vartheta y_{t-1} + \varepsilon_t$$
$$\varepsilon_t = \alpha_t e_t, e_t \sim I.I.D\ (0,1)$$

where $\alpha_t$is the conditional standard deviation, e_t is a white noise process, and ε_t is the error term. In addition to the normal distribution, we take into account two heavy-tailed distributions for the white noise e_t: the Student's t distribution and the normal inverse Gaussian (NIG)

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distribution.As a subgroup of the generalized hyperbolic distribution, the NIG distribution was identified by Barndorff-Nielsen [38]. Its tail is lighter than the Student's t distribution but fatter than the normal distribution. The NIG distribution has been incorporated into GARCH models in numerous studies over the last 20 years in order to suit a range of asset series, including exchange rate dynamics [39], stock returns [40], and oil future prices [41]. We wish to examine the NIG distribution for Nifty 50 index due to its widespread use. The NIG distribution's probability density function (PDF) is provided by

$$f(e_t) = \frac{\vartheta \gamma K_1 \sqrt[\vartheta]{\gamma^2 + (e_t - \mu)^2}}{\sqrt[\pi]{\gamma^2 + (e_t - \mu)^2}} exp\left(\sqrt[\vartheta]{\vartheta^2 - s^2} + s(e_t - \mu)\right)$$

where $Kj(\bullet)$ is a third-kind modified Bessel function. The shape and skew parameters are denoted by the letters s and ϑ, respectively, and $\mu = -\gamma s/\sqrt{\vartheta^2 - s^2}$ and $\gamma = \left(\sqrt{\vartheta^2 - s^2}\right)^3/\vartheta^2$. Additionally, we control the distribution's form by using the parameter ϑ to indicate the Student's t distribution's degree of freedom.The GARCH models utilized in this study are listed in Table 1, along with the original authors of each model found in the literature. Applying these GARCH models to explain the volatility dynamics of Nifty 50 index return has recently sparked renewed attention. Some of these studies include [42-44]. In line with this pattern, our study aims to explain the volatility dynamics of Nifty 50 index return. These models are intended to reflect the well-known stylized facts volatility clustering, leptokurtosis, and non-zero skewness found in financial data. We will not go into great depth about these models here because they are established standard models. The findings are generally compatible with other popular GARCH-type models, including APARCH in Ding, Granger, and Engle [45] and CGARCH in Lee and Engle [46]. Due to space constraints, we are unable to disclose their findings. The maximum likelihood estimation (MLE) approach is used to estimate the models. The Pearson goodness-of-fit test has also been used to determine if a sample's residual frequency distribution aligns with a specific theoretical distribution. The distribution of the test statistic under the null hypothesis of a correctly described model is $\chi(g - 1)$, where g is the number of bins.

Table 1: *GARCH model list*

Model	Volatility Calculation	Anticipated by
GARCH	$\sigma_{t+1}^2 = \varphi + \theta\varepsilon_t^2 + \delta\sigma_t^2$	Bollerslev [47]
EGARCH	$log(\sigma_{t+1}^2) = \varphi + \theta(\lvert\varepsilon_t\rvert - E(\lvert\varepsilon_t\rvert)) - \rho\varepsilon_t + \delta log(\sigma_t^2)$	Nelson [48]
IGARCH	$\sigma_{t+1}^2 = \varphi + \theta\varepsilon_t^2 + (1-\theta)\sigma_t^2$	Engle and Bollerslev [47]
TGARCH	$\sigma_{t+1} = \varphi + \theta\sigma_t(\lvert\varepsilon_t\rvert - \tau\varepsilon_t) + \delta\sigma_t$	Zakoian [49]
GJR-GARCH	$\sigma_{t+1}^2 = \varphi + \theta\varepsilon_t^2 + \tau I(\varepsilon_t < 0)\varepsilon_t^2 + \delta\sigma_t^2$	Glosten, Jagannathan, and Runkle [50]

We also use the risk metric, Value at Risk (VaR), to assess the GARCH models for Nifty 50 index return series from a risk management standpoint. To manage the risk of Nifty 50 index return, VaR is frequently utilized in both industry and academics [51-52]. Our goal is to use VaR to control the risk of Nifty 50 index return positions in accordance with the literature. The following defines the VaR for the confidence level pis:

$$VaR_p(b_{t+1}) = inf\{b\epsilon\mathcal{R}: P(b_{t+1} > b) \leq 1 - p/\phi_t\}$$

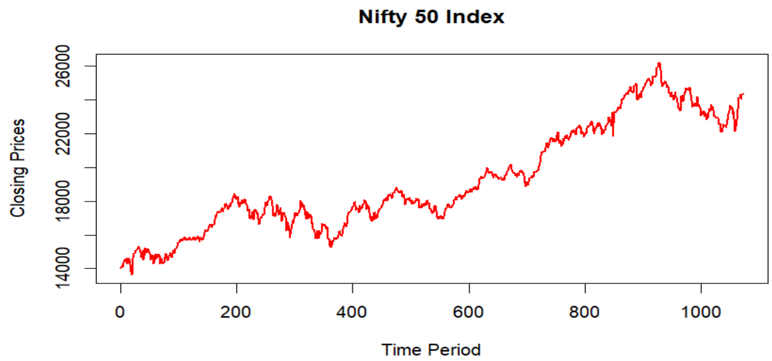
where ϕ_t represents the information set at time t and $p \in (0,1)$ represents the confidence level. As part of their market risk management procedures, financial institutions have started calculating historical VaR1 using data spanning one year. The primary approach have been widely used in the industry: the parametric approach [53].

The parametric approach involves estimating the GARCH model with the normal distribution (GARCH-Normal) and the GARCH-NIG model on a rolling window of one year. The computed models are then used to compute one-day ahead VaR estimations at various confidence levels. The GARCH-Normal model primarily acts as a benchmark, while the GARCH-NIG model is of greater importance to us. Then, using the parametric approaches, we compare the VaR estimates with the actual observation. Daily exceedances over 95%, 97.5%, and 99% for both long and short positions are summarized for each Nifty 50 index return series. The summarized daily exceedances are then subjected to the Christoffersen's [54] and Kupiec's tests [55]. The Christoffersen's test additionally takes into account the conditional likelihood between consecutive days, whereas the Kupiec's test just concentrates on the unconditional probability of seeing an exceedance.

III. Result and Discussions

I. Data Collection

This study examines the NSE NIFTY 50 Index, which represents a diversified portfolio of the 50 largest and most liquid stocks listed on the National Stock Exchange (NSE) of India. Serving as a key benchmark for the Indian equity market, the NIFTY 50 Index reflects the overall performance of the market and provides insight into the economic condition of India. The study utilizes daily closing prices of the NIFTY 50 Index, obtained from the official NSE website, to ensure data accuracy and consistency for robust statistical analysis. It includes 1072 observations of closing prices for the NSE Nifty index between January 1, 2021, and April 31, 2025. We calculate the return series, $ln(btc_t/btc_{t-1})$(first difference of the natural logarithmic series), where btc_t and btc_{t-1} represent the prices at t and $t-1$, respectively. To illustrate how Nifty 50 index and returns have changed over time, Figure 1. depicts the Nifty 50 index daily return series.



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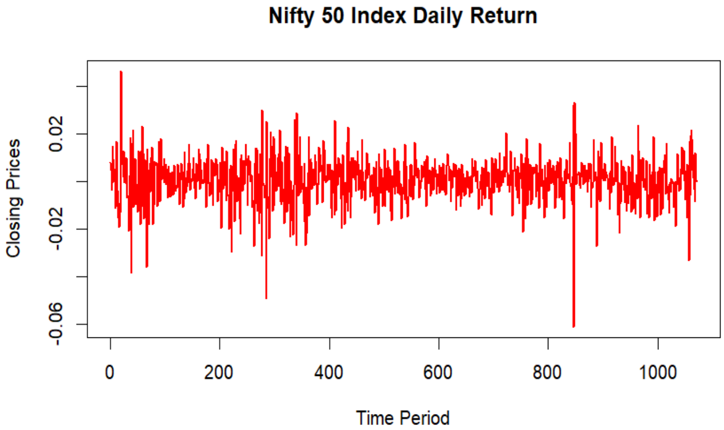

Figure 1: *Nifty 50 index and return plots*

II. Descriptive Statistics and Unit Root Test

The unit root analysis and descriptive statistics for the return series are shown in Table 2. We use the Phillips-Perron (PP) and Augmented Dickey-Fuller (ADF) unit root tests on the return series to evaluate the series' stationary characteristics. All return series reject the null hypothesis that the series has a unit root, according to the findings of the ADF test. The null hypothesis is rejected based on the results of the PP test, which demonstrate that all return series are stationary. Consequently, for the empirical analysis, we choose the return series.

Table 2: *Descriptive statistics and unit root test for Nifty index return series.*

	Nifty 50 index return
Mean	0.0421
Median	0.0593
Maximum	10.17
Minimum	-0.06
Std. Dev.	1.395
Skewness	-0.515
Kurtosis	4.01
Jarque-Bera	770.23
Probability	0.000***
ADF test	-10.848 (0.000) ***
PP test	-1010.7 (0.000) ***

Author calculation: * stands for 1% level statistical significance.

The mean values for the Nifty 50 index return series are positive. Even yet, Nifty 50 index and return has a negative skewness. The return series' kurtosis exceeds 3. Consequently, the majority of results are leptokurtic and skewed. The normalcy assumption for Nifty 50 index and return series is denied, according to the statistically significant Jarque–Bera (JB) test results. In order to get more robust estimation results, we apply the normal distribution (GARCH-Normal) and the GARCH model with the normal inverse Gaussian distribution (GARCH-NIG) to these return series with a normal distribution.

III. Model Estimation

The estimated outcomes of the GARCH algorithms for the Nifty 50 index return series are shown in Table 3. The estimations' p-values are shown by the figures in parentheses. Only when g equals 30 do we provide the outcomes of the Pearson goodness-of-fit test. Our results are constant when g = 20 or 50, despite the common belief that the Pearson goodness-of-fit assessments are sensitive to the value of g. The findings are summed up as follows. First, the heavy-tailed distributions perform significantly better than the normal distribution in fitting the returns of Nifty 50 index return, as shown by the log-likelihoods and AICs.

Table 3: *Outcomes of GARCH model estimation*

Model	GARCH-Normal	GARCH-NIG
ϕ	0.0027 (0.003)	-0.000285 (0.88)
$100 *_{\varphi}$	0.0033 (0.00)	0.0079 (0.281)
θ	0.130 (0.00)	0.0107 (0.081)
δ	0.868 (0.00)	0.6038 (0.00)
Skew	-	-0.069 (0.618)
Shape	-	0.010 (0.00)
Log likelihood	3376.449	3814.376
AIC	-3.4660	-3.9141
$\chi^2(g.test)$	468.4*	46.4

Author calculation: The p-value of the estimate is the value included in parenthesis. * Stands for 1% level statistical significance.

Additionally, for the Nifty 50 index return series, the GARCH-NIG model has the lowest AIC among the GARCH models, and the NIG distribution performs marginally better than the Student's t distribution. Secondly, the results of the Pearson goodness-of-fit test verify that, for the Nifty 50 index return series, the NIG distribution has the best sample performance among the GARCH-NIG distribution (GARCH-NIG) and cannot be rejected. Finally, all three parameters $\phi, \gamma,$ and skew are statistically or marginally significantly different from zero, but the great majority of the predicted parameters are not. In contrast to recent evidence in the Nifty 50 index, which shows that return volatilities of the Nifty 50 index return increase more in response to positive shocks than in response to negative shocks [56], the results for the Nifty 50 index return show that return volatilities do not increase more in response to positive shocks than in response to negative shocks.

The outcomes of the parametric approaches of the Christoffersen's and Kupic's tests for the Nifty 50 index return series are compiled in Table 4. The findings show that both the Kupiec's test and the Christoffersen's test reflect seven rejections at a 5% confidence level, notwithstanding the VaR estimations based on the GARCH-Normal model. On the other hand, we are unable to reject the null hypothesis at a

5% confidence level for any of the VaR estimates that are taken into consideration when using the GARCH-NIG model. All things considered, we draw the conclusion that the GARCH-NIG model may produce precise VaR estimates for the return series of Nifty 50 index.

Table 4: *Outcomes of Backtesting*

Models	GARCH-Normal	GARCH-NIG
Kupic's test		
VaR95short	9.07**	0.78
VaR95long	0.67	0.36
VaR97.5short	0.65	0.75
VaR97.5long	3.54	0.87
VaR99short	2.16	0.30
VaR99long	9.45**	1.87
Christoffersen's test		
VaR95short	7.45**	0.96
VaR95long	2.74	0.63
VaR97.5short	1.20	1.01
VaR97.5long	3.97	1.76
VaR99short	1.54	0.62
VaR99long	9.87**	2.45

Author calculation: * stands for 1% level statistical significance.

IV. Conclusions

In this paper, we employ GARCH models to experimentally analyze the quantitative risk management of the Nifty 50 index returns, focusing on volatility dynamics within the Indian market. The Nifty 50 return series was constructed by classifying futures contracts based on time to maturity, and GARCH models were fitted to this data. Our results indicate that incorporating heavy-tailed distributions into the GARCH framework is essential to adequately capture the observed non-normality and volatility clustering in the returns. Moreover, we find that the volatility response of the Nifty 50 returns to positive and negative shocks is symmetric, differing from patterns observed in some other markets. We also evaluate Value-at-Risk (VaR) estimates using parametric methods based on GARCH models with both normal and Normal Inverse Gaussian (NIG) distributions. Although the parametric VaR estimates are generally reliable and outperform the standard GARCH-Normal model, the GARCH-NIG model delivers the most accurate VaR predictions. In summary, the study demonstrates that the GARCH-NIG model provides precise volatility modeling and risk measurement for the Nifty 50 index returns, making it a valuable tool for risk managers and policymakers in the Indian financial market. The main goal of this study is to examine how the Nifty Index option affects the volatility of the Indian stock market. The study may be expanded by looking at the spillover of volatility between nations. Additionally, high-frequency data on the impact of stock options trading might be utilized for additional research.

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