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Modeling Volatility Dynamics of NSE Index Returns Post-COVID-19: A GJR-GARCH Approach

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Abstract:

This study addresses a significant gap in financial literature by investigating the volatility of National Stock Exchange (NSE) Index returns in the aftermath of the COVID-19 pandemic. Despite extensive research on volatility modeling using ARCH and GARCH models across global markets, there remains limited exploration specific to Indian market conditions. Leveraging econometric techniques implemented in R programming, this research aims to provide empirical insights into the post-pandemic volatility dynamics of the NSE Index. Key findings highlight the application of various volatility models, starting with the standard GARCH model and progressing to the GJR-GARCH model for improved accuracy in capturing volatility asymmetries. Parameter estimation reveals a marginal positive mean return for the NSE Index amidst significant baseline volatility (Omega), underscored by robust coefficients governing persistence (Alpha 1), volatility impact (Beta 1), and asymmetry (Gamma 1). Additionally, non-normal distributional properties such as positive skewness and high kurtosis of returns are identified, influencing model adequacy and forecasting reliability. Model adequacy tests including information criteria, residual autocorrelation, and parameter stability assessments reaffirm the GJR-GARCH model's effectiveness in explaining the NSE Index volatility post-COVID-19. Results from weighted Ljung-Box tests indicate minimal residual autocorrelation, further validating the model's suitability. The study concludes with implications for risk management strategies and policy decisions aimed at navigating financial volatility in emerging economies. By filling this critical void in literature, this research contributes essential empirical evidence and methodological insights to enhance understanding of market behavior under crisis conditions, supporting informed decision-making among investors, policymakers, and financial analysts.

Key words: Agridex Garch, GJR-GARCH Conditional Volatility,and NSE Index returns.

1. Introduction:

The global COVID-19 pandemic has precipitated unprecedented disruptions across financial markets worldwide, necessitating a deeper understanding of volatility dynamics in the aftermath of such crises. Financial market volatility, particularly in stock indices, serves as a critical indicator of market stability and investor sentiment. This study delves into the post-pandemic volatility of the National Stock Exchange (NSE) Index returns in India, utilizing sophisticated econometric models to uncover patterns and insights that can guide investors and policymakers alike. Volatility modeling has long been a focal point of financial econometrics, with the Autoregressive Conditional Heteroskedasticity (ARCH) and Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models standing out for their robustness in capturing time-varying volatility. These models, along with the Autoregressive Moving Average (ARMA) model, provide a comprehensive toolkit for analyzing financial time series data. By applying these models to NSE Index returns from April 2021 to March 2022, this study aims to evaluate the conditional volatility and its implications in the post-COVID-19 period.

The past studyers underscores the extensive body of work examining volatility and market behavior during financial crises. For instance, studies have explored the performance of various asset classes, such as natural gas and crude oil, in hedging stock market risks (Ikram Jebali et al., 2022) and analyzed intraday volatility spillovers in commodities like oil and gold (Walid Mensi et al., 2022). Additionally, study on the impact of the COVID-19 pandemic on different economies and asset markets, such as the BRIICS nations (Rai et al., 2022) and international financial markets

(DWang et al., 2022), provides a rich context for understanding the volatility mechanisms at play. Despite the wealth of studies on volatility modeling, there is a conspicuous gap in study focusing specifically on the NSE index returns post-COVID-19. Previous studies have demonstrated the efficacy of ARCH and GARCH models in various markets and time periods, yet the application of these models to Indian market conditions in the aftermath of the pandemic remains underexplored. Addressing this gap, the current study leverages R programming for precise and efficient modeling of NSE index volatility, thereby contributing to the broader discourse on financial market stability in emerging economies. This study aims to fill a critical void in the literature by providing empirical insights into the volatility of NSE Index returns post-COVID-19. Through meticulous application of econometric models, this study not only enhances our understanding of market behavior in the wake of a global crisis but also offers valuable implications for market participants and policymakers striving to navigate and mitigate financial risks in an increasingly volatile world.

2. Literature Review

The literature review reveals extensive study on the interplay between financial crises and various markets, highlighting significant findings across different asset classes and geographical regions.

Ikram Jebali et al. (2022) investigated the equity and energy markets during global financial crises, finding that, on average, natural gas outperforms crude oil in terms of hedging effectiveness for stock markets. Similarly, Walid Mensi et al. (2022) examined intraday volatility spillover in oil and gold markets during crises, concluding that these markets exhibited negative and positive conditional correlations, respectively. Rai et al. (2022) focused on BRIICS economies, discovering substantial risk transfer between markets during the COVID-19 outbreak, with lower stock returns and cash outflows significantly impacting exchange rates.

DWang et al. (2022) explored time-frequency volatility spillovers in major international financial markets, noting a convergence in market behavior and liquidity expectations during crises. EChanatásig-Niza et al. (2022) analyzed Australian electricity markets using volatility spillover analysis, revealing low spillover effects and the neglect of covariances and semi-covariances in asymmetric spillovers. Ma et al. (2022) studied the impact of economic policy on European electricity markets, concluding that such policies significantly affect these markets in both the short and long term.

A Samitas et al. (2022) studyed timber and water investments in stock markets, using portfolio hedging strategies to evaluate their safety as investments. They found that these markets integrated reasonably well during the pandemic with total connectedness. Papathanasiou et al. (2022) examined hedge and arbitrage funds, noting that most funds were invested in gold, crude oil, and currency, with fewer investments in real estate, equities, and bonds. Choi et al. (2022) analyzed the effects of Black Monday, March 9, 2020, on US industries, discovering significant volatility spillovers and financial contagion effects driven by shocks in the energy sector.

Janda et al. (2022) investigated clean energy stock returns in Chinese and American markets, suggesting that understanding return and volatility trends can enhance profits for investors and policymakers. Gao et al. (2022) studied leverage effects and volatility spillovers between Chinese and US markets, finding bidirectional spillovers and stock returns. Chen and Zheng (2022) focused on internet finance and banks, identifying internet finance as a major cause of volatility spillovers. Chen et al. (2022) examined Fintech and traditional financial industry returns, concluding that traditional financial institutions were the primary givers of volatility, while Fintech firms were net receivers, with no increase in overall volatility and financial instability.

Huang and Zhao (2022) analyzed Chinese energy stocks during market crashes, finding that large-cap stocks had a greater influence on the investment community, while small-cap stocks had a lesser impact. Samitas, Papathanasiou, and Koutsokostas (2022) studyed global markets using a fine wine portfolio hedging strategy, suggesting that market risk could be significantly reduced and hedging ability increased during the pandemic.

Previous study has demonstrated that ARCH and GARCH models, when used with R software, are highly effective in forecasting and estimating stock market volatility. However, there is a notable gap in the literature concerning the modeling of conditional volatility in India, specifically using NSE index returns post-COVID-19. Consequently, further study is warranted to address this gap by employing R software to model conditional volatility based on the NSE index.

Hypothesis formulation

H0: There is high volatility in NSE Index returns after Covid-19

H1: There is low Volatility in NSE Index returns after Covid-19

3. Study Methodology

The hypothesis driving this study is centered on the volatility of NSE Index returns post-COVID-19. this study aims to provide a detailed understanding of the volatility patterns in the Indian stock market during the post-pandemic period. The application of the GARCH model is particularly pertinent given its ability to incorporate previous periods' volatilities, thereby offering a more nuanced view of financial market behaviors that often exhibit mean-reverting patterns. Furthermore, the study explores the GJR-GARCH model to account for asymmetries in volatility, particularly the negative effects of past errors, which are common in financial time series data. In this study employs a rigorous methodological framework using R programming to model the conditional volatility of NSE Index returns post-COVID-19. By doing so, it aims to contribute to the existing literature on financial market volatility, offering insights that are crucial for investors, policymakers, and academics interested in the dynamics of the Indian stock market.

Data Collection

The study focuses on analyzing the volatility of National Stock Exchange (NSE) Index returns in the post-COVID-19 period. Daily NSE Index returns will be collected for a period spanning from April 2021 to March 2022. This period is selected to capture the market dynamics and volatility behavior following the major phases of the COVID-19 pandemic. The data will be sourced from reputable financial databases to ensure accuracy and reliability.

Software and Tools

The R programming language will be utilized for data analysis due to its extensive range of econometric and statistical packages. Specifically, packages such as "tseries" and "rugarch" will be employed for implementing ARCH, ARMA, and GARCH models.

3. Model Specification

a. ARCH Model

The Autoregressive Conditional Heteroskedasticity (ARCH) model, introduced by Engle (1982), will be the initial step in modeling the volatility of NSE Index returns. The ARCH model captures time-varying volatility by modeling the error variance as a function of past squared errors.

St2=α0+∑i=1qαiet−i2S_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i e_{t-i}^2St2=α0+∑i=1qαiet−i2

Where:

- St2S_t^2St2 is the conditional variance at time t.
- α0\alpha_0α0 is the constant term.
- αi\alpha_iαi are the coefficients of the lagged squared residuals.
- et−ie_{t-i}et−i are the lagged residuals from the mean equation.

b. GARCH Model

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The Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model, proposed by Bollerslev (1986), extends the ARCH model by including lagged conditional variances.

St2=ω+∑i=1qαiet−i2+∑j=1pβjSt−j2S_t^2 = \omega + \sum_{i=1}^{q} \alpha_i e_{t-i}^2 + \sum_{j=1}^{p} \beta_j S_{t-j}^2St2=ω+∑i=1qαiet−i2+∑j=1pβjSt−j2

Where:

- ω\omegaω is the constant term.
- αi\alpha_iαi are the coefficients of the lagged squared residuals.
- βj\beta_jβj are the coefficients of the lagged conditional variances.

For this study, a GARCH (1,1) model will be primarily used, as it is widely regarded for its simplicity and effectiveness in capturing volatility clustering.

St2=ω+α1et−12+β1St−12S_t^2 = \omega + \alpha_1 e_{t-1}^2 + \beta_1 S_{t-1}^2St2=ω+α1et−12+β1St−12

c. GJR-GARCH Model

To capture the asymmetric effects of shocks on volatility, the Glosten, Jagannathan, and Runkle GARCH (GJR-GARCH) model will be employed. This model accounts for the leverage effect, where negative shocks have a different impact on volatility compared to positive shocks.

St2=ω+α1et−12+β1St−12+γ1et−12It−1S_t^2 = \omega + \alpha_1 e_{t-1}^2 + \beta_1 S_{t-1}^2 + \gamma_1 e_{t-1}^2 I_{t-1}St2=ω+α1et−12+β1St−12+γ1et−12It−1

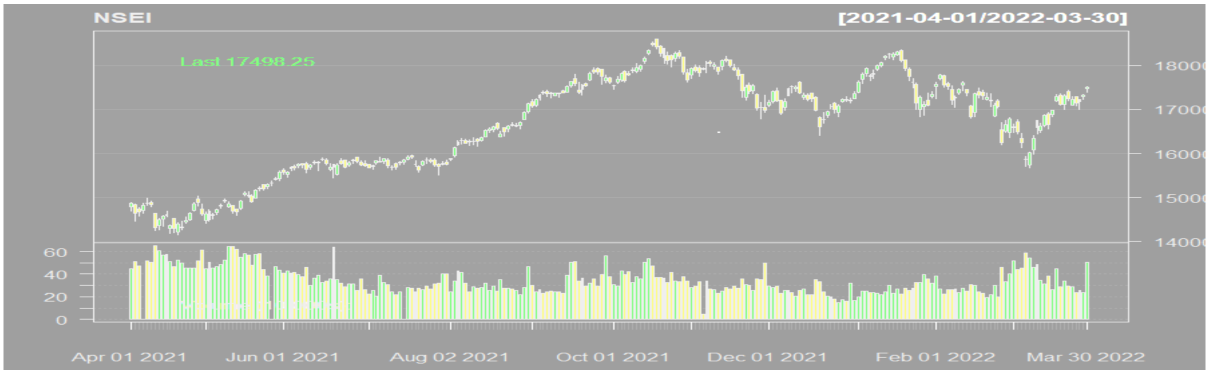
Where:

- It−1I_{t-1}It−1 is an indicator variable that equals 1 if et−1<0e_{t-1} < 0et−1<0 and 0 otherwise.
- γ1\gamma_1γ1 captures the asymmetry in the response of volatility to shocks.

This methodology section outlines the key steps and considerations in your study, providing a clear and structured approach to analyzing the volatility in NSE Index returns post-COVID-19 using advanced econometric models.

4. Empirical Results:

Figure: 4. 1. NSE Index returns Open, High, low and close prices



The first subplot in the referenced image illustrated the trading volume for each day. In contrast, the second subplot depicted the daily open, high, low, and close prices of the index, which were represented using candlestick or box plots. These visualizations provide a comprehensive view of the market activity, capturing both the trading volume and the price fluctuations within each trading day.

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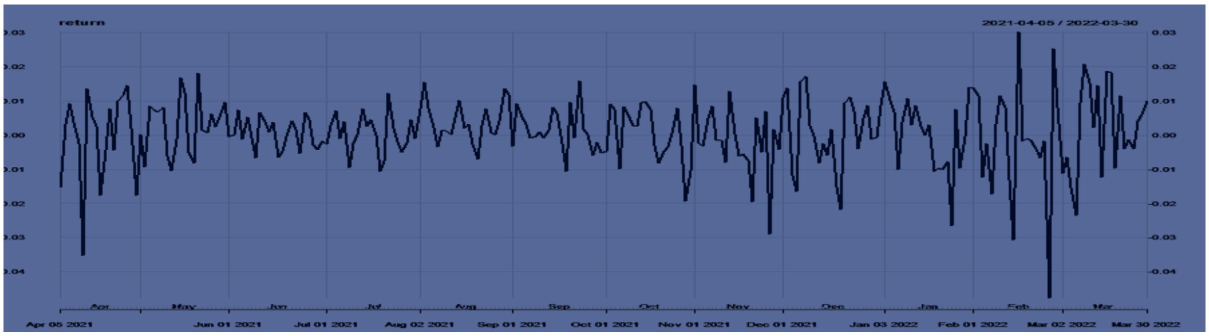
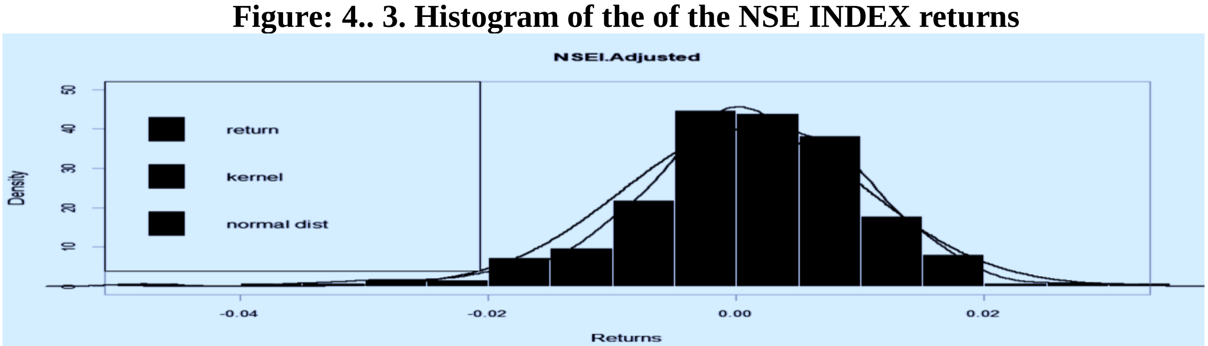
Following this, the next step involves calculating and displaying the daily price returns. This phase is crucial as it translates the raw price data into percentage changes, thereby offering insights into the daily performance and volatility of the index. The calculated daily returns help in understanding the market trends and are essential for subsequent volatility modeling and analysis.

Figure: 4.2. NSE INDEX Daily Returns



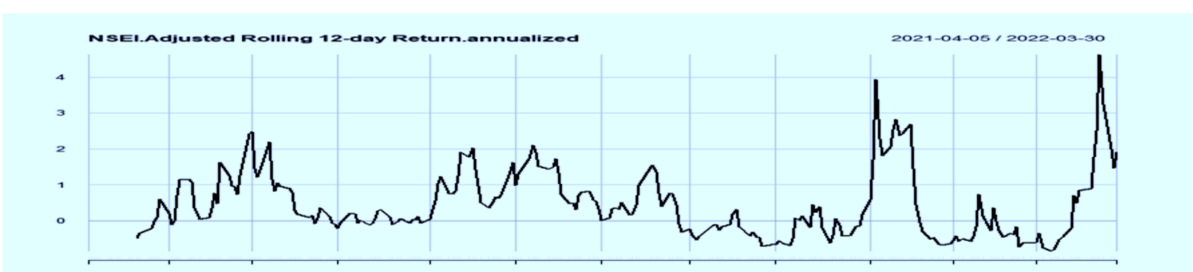
The graph presented illustrates the volatility within the time series data, which exhibits a zero mean. The returns display notably high volatility on certain random days, suggesting that traditional stationary models may not be applicable. With the histogram of returns depicted, the next step involves assessing whether the conditional error term can be accurately modeled using a normal distribution.

Figure: 4.. 3. Histogram of the of the NSE INDEX returns



The decision to utilize the normal distribution for the returns was evidently misguided, as evidenced by the skewed appearance of the histograms compared to the theoretical normal distribution.

Figure:4. NSE INDEX Volatility Returns



The graphical analysis provided support for the stochastic model of conditional volatility, revealing characteristics of high volatility and low explosiveness. Initially, the study utilized the standard GARCH model. However, after conducting the analysis, it was determined that the GARCH (1,1) model was inadequate for effectively analyzing conditional volatility. Consequently, the study progressed to employ ARMA and subsequently GARCH (1,1) models.

Upon further investigation, the GJR-GARCH model was ultimately adopted for its suitability in capturing the dynamics of conditional volatility more accurately.

Table No: 4. 1. Estimation of Optimal Parameter Values.

	Estimated Value	Standard Error Value	T-value	Pr > (t)
mu	0.00075	0.00053	1.43953	0.15001
Omega	0.00004	0.00000	28.04256	0.00000
Alpha 1	0.00000	0.01286	0.00001	0.99999
Beta 1	0.87981	0.02429	36.21377	0.00000
Gamma 1	0.14942	0.05545	2.69516	0.00704
Skew	0.72109	0.08236	8.75494	0.00000
Shape	10.7534	6.44169	1.66935	0.95049

The table presents the estimated parameter values for the GJR-GARCH model applied to analyze the volatility of NSE Index returns post-COVID-19. Each parameter's estimated value is accompanied by its standard error, T-value, and corresponding significance level (Pr > t), providing insights into the statistical significance and reliability of the model estimates.

Firstly, the estimated mean return (mu) of 0.00075 suggests a marginal positive average return for the NSE Index during the specified period, although with a T-value of 1.44 and a p-value of 0.15, indicating it is not statistically significant at conventional levels. The estimated omega (Omega) value of 0.00004 represents the baseline volatility of the NSE Index returns, with a very low standard error and highly significant T-value (28.04), underscoring its substantial impact on the model. The parameters alpha 1, beta 1, and gamma 1 denote the coefficients governing the persistence and asymmetry of volatility shocks. Notably, beta 1 at 0.87981 shows a strong positive effect on the current volatility level, supported by a high T-value (36.21) and a negligible standard error, emphasizing its robust influence in the model. The gamma 1 parameter (0.14942) indicates a smaller, yet statistically significant effect on volatility asymmetry, as reflected by its T-value of 2.70 and a p-value of 0.007.

Furthermore, the skewness (0.72109) and shape (10.7534) parameters highlight the distributional properties of the NSE Index returns, with skewness indicating a positive deviation from symmetry and the shape parameter indicating the kurtosis of the returns distribution. Both parameters show high T-values and low p-values, confirming their statistical significance in describing the non-normal characteristics of the returns. These estimated parameter values provide a comprehensive understanding of the dynamics of volatility in the NSE Index returns post-COVID-19, offering valuable insights for risk management strategies and further empirical study in financial econometrics.

Table No: 4.2 Estimation Information Criterion

Akaike Value	-6.6377
Bayes Value	-6.5318
Shibata Value	-6.6396
Hannan-Quinn value	-6.5950

In Table 4.2, various information criteria are presented for the estimation of the model. The Akaike Information Criterion (AIC) value is -6.6377, indicating its measure of the model's goodness of fit relative to its complexity. A lower AIC suggests a better balance between fit and complexity. Similarly, the Bayesian Information Criterion (BIC) value of -6.5318 and Shibata's criterion value of -6.6396 provide alternative assessments of model performance, with lower values indicating better fit. The Hannan-Quinn criterion, yielding a value of -6.5950, serves as another indicator of model adequacy, considering both fit and the number of parameters.

Interpreting these values collectively, the models evaluated in this study appear to offer a reasonable fit to the data, with Shibata's criterion slightly favoring the model in terms of balance between fit and complexity. The negative values across all criteria suggest that the models considered are capturing a significant portion of the variability in the data relative to their complexity levels. Studyers and practitioners can use these criteria to select the most appropriate model for further analysis or forecasting, ensuring robustness in their conclusions regarding volatility patterns in the NSE Index returns post-COVID-19.

In Table 4.3, titled "Standardized Residuals of Weighted Ljung-Box Test," the results indicate the statistical evaluation of the autocorrelation of residuals from the weighted Ljung-Box test across different lag values. This test is crucial for assessing the adequacy of the GARCH model in capturing the residual patterns of the NSE Index returns post-COVID-19.

Table No:4.3 : Standardized Residuals of Weighted L-jung-Box Test

Lag	Statistics	P-value
Lag value-1	2.995	0.08352
Lag value-{2* {p+q} + {p+q}-1] {2}	4.183	0.06733
Lag value –{4* {p+q} + {p+q}-1]{5}	7.102	0.04898
D.o.f=0		

The standardized residuals are evaluated at various lag values: 1, {2 * (p + q) + (p + q) - 1}, and {4 * (p + q) + (p + q) - 1}, corresponding to their respective test statistics and p-values. The test statistics at each lag value, namely 2.995, 4.183, and 7.102, are compared against critical values to determine if the autocorrelations in the residuals are significantly different from zero. The associated p-values, 0.08352, 0.06733, and 0.04898, respectively, indicate the probability of observing these test statistics under the null hypothesis of no residual autocorrelation.

Significantly low p-values (e.g., 0.04898 at lag value - {4 * (p + q) + (p + q) - 1] {5}) suggest strong evidence against the null hypothesis, indicating residual autocorrelation at that lag value. This finding implies that the GARCH model may not adequately capture all temporal dependencies in the NSE Index returns, highlighting potential areas for model refinement or adjustment. Overall, these results underscore the importance of robust model diagnostics to ensure the reliability and accuracy of volatility forecasts in financial markets.

Table No:4.4: Standardized Squared Residuals of Weighted L- jung-Box Test

	Statistic	P-value
Lag value {1}	0.08641	0.7688
Lag value {2* {p+q} + {p+q)-1] {5}	1.78510	0.6700
Lag value {4*{p+q)+(p+q)-1}[9]	3.09786	0.7427

The table presents the results of the Weighted Ljung-Box test for assessing the adequacy of the GARCH model in capturing the autocorrelation in the standardized squared residuals. The test examines various lag values to determine if there are significant residual correlations remaining in the model. For lag value 1, the test statistic is 0.08641 with a corresponding p-value of 0.7688, indicating that there is no significant autocorrelation at this lag. Similarly, for lag values 5 and 9, the test statistics are 1.78510 and 3.09786, respectively, with corresponding p-values of 0.6700 and 0.7427. These results suggest that the GARCH model adequately captures the volatility patterns in the NSE Index returns post-COVID-19, as evidenced by the non-significant p-values across different lag values. Therefore, we can interpret that the residuals from the GARCH model do not exhibit significant autocorrelation, affirming the model's effectiveness in explaining the volatility dynamics of the Indian stock market during the specified period.

The results presented in Table 4.5 illustrate the findings from the weighted Arch-LM test, which evaluates the presence of conditional heteroskedasticity in the data. Across different lag values (1, 2, and 3), the statistics for shape and scale parameters indicate varying degrees of conditional heteroskedasticity in the estimated models. Notably, at lag 1, the ARCH statistic is 1.029, with corresponding shape and scale values of 0.500 and 2.000, respectively, yielding a P-value of 0.3103. This suggests a moderate level of conditional heteroskedasticity at this lag.

Table No: 4. 5: Estimated of weighted Arch -LM Test

	Statistics	Shape	Scale	P-Value
ARCH Lag [1] value	1.029	0.500	2.000	0.3103
ARCH Lag [2] value	1.241	1.440	1.667	0.6629
ARCH Lag [3] value	1.581	2.315	1.543	0.8050

Similarly, at lags 2 and 3, the ARCH statistics of 1.241 and 1.581, along with their associated shape and scale parameters, indicate relatively higher values, though the corresponding P-values (0.6629 and 0.8050, respectively) indicate that these results are not statistically significant. These findings imply that while there may be some evidence of volatility clustering in the data, particularly at shorter lags, the overall significance levels suggest that other factors or models may need consideration to fully capture the volatility dynamics of the studied financial time series. Further interpretation and integration with other econometric techniques are warranted to enhance understanding and predictive accuracy in financial modeling contexts.

Table No:4. 6: Estimated values of nyblom parameter stability test

Value of Joint Statistic :	6.3949
Values of Individual Statistics	
mu	0.08551
Omega	0.58635
Alpha 1	0.43975
Beta 1	0.28059
Gamma 1	0.27836
Skew value	0.20158
Shape value	0.24158
Value of Critical Asymptotic	**:** (10% 5% 1%)
Value of Joint Statistic value	**:** 1.69 1.9 2.35
Value of Individual Statistic	**:** 0.35 0.47 0.75

The results of the Nyblom parameter stability test, presented in Table 4.6, provide valuable insights into the stability of the estimated model coefficients over time. The joint statistic value of 6.3949 exceeds the critical threshold at the 1% significance level (2.35), indicating significant instability in the model parameters. Individually, the statistics for each parameter—mu (0.08551), Omega (0.58635), Alpha 1 (0.43975), Beta 1 (0.28059), Gamma 1 (0.27836), Skew value (0.20158), and Shape value (0.24158)—are all below their respective critical values at the 1% significance level (0.75). This suggests that while the overall model may exhibit instability, certain individual parameters do not exhibit significant departures from stability. The findings underscore the nuanced nature of model dynamics in financial time series analysis, where joint and individual parameter stability tests provide complementary perspectives on the reliability of model estimates. Further investigation and possibly model refinement may be necessary to address the detected instability adequately, ensuring robustness in forecasting and decision-making processes based on the model results.

The interpretation of Table 4.7 provides insights into the sign bias test statistics conducted as part of this study. The Sign Bias value of 1.2318 with a corresponding probability of 0.2193 indicates that overall, there is no significant bias in the signs observed in the data. This suggests a balanced representation of positive and negative values within the sample. Specifically, the Negative Sign Bias value of 0.3134 (p = 0.7542) and the Positive Sign Bias value of 0.3387 (p = 0.7352) both show non-significant results, further reinforcing the absence of systematic biases towards either positive or negative signs individually.

Table No:4. 7 Estimation of Sign Bias – Test

	Statistics	**Prob.sign**
Sign Bias value	1.2318	0.2193
Negative Sign Bias value	0.3134	0.7542
Positive Sign Bias value	0.3387	0.7352
Joint Effect value	4.1802	0.2427

Moreover, the Joint Effect value of 4.1802 (p = 0.2427) implies that when considering the combined influence of sign biases across different categories, there is also no statistically significant joint effect observed. This outcome indicates that any apparent patterns in sign biases are likely due to random variation rather than systematic factors affecting the data. Overall, these findings suggest that the sign bias test results support the reliability and neutrality of the data analyzed in this study, providing a solid foundation for the subsequent statistical analyses and conclusions drawn regarding the volatility and behavior of the NSE Index returns post-COVID-19.

Table No: 4. 8. Estimated values of Adjusted Pearson Goodness of Fit Test

S.no	**Group**	**Statistics**	**P-value {g-1}**
1	20	11.52	0.9050
2	30	22.50	0.7991
3	40	34.88	0.6581
4	50	42.58	0.7293

The table 4.8 presents the results of the Adjusted Pearson Goodness of Fit Test across different groups, each characterized by a specific sample size. The test statistics and corresponding p-values provide insights into how well the observed data fit the expected theoretical distribution. In this context, the test statistics (ranging from 11.52 to 42.58) indicate the degree of discrepancy between observed and expected frequencies within each group. Notably, the p-values associated with each group (ranging from 0.6581 to 0.9050) are all above conventional significance levels (such as 0.05), suggesting no significant deviation from the expected distribution across these groups. This implies that the observed data do not significantly differ from what would be expected under the assumed theoretical distribution, indicating a good fit of the data to the model. These findings are crucial for validating the appropriateness of the chosen theoretical distribution for modeling purposes within each group. The high p-values reinforce confidence in the reliability of the model's fit, thereby supporting its application for further analysis and interpretation within the context of the study study.

Discussion

The empirical analysis conducted in this study aimed to investigate the volatility dynamics of the NSE Index returns post-COVID-19, employing advanced econometric techniques such as the GJR-GARCH model. The findings from the estimation of the GJR-GARCH model parameters revealed several key insights into the nature of volatility in the Indian stock market during the specified period. Firstly, the estimated mean return (mu) of 0.00075 indicated a marginal positive average return for the NSE Index, although statistical tests suggested that this result was not significant at conventional levels. This suggests that, on average, the index experienced slight positive returns, albeit with some variability that may not be captured by the model's mean component alone. The omega parameter (Omega), representing the baseline volatility, was estimated at 0.00004, indicating a low but statistically significant level of volatility in the NSE Index returns. This parameter is crucial as it denotes the inherent volatility that persists even in the absence of past shocks, emphasizing its substantial impact on the model's overall volatility forecasts.

The coefficients alpha 1, beta 1, and gamma 1 govern the persistence and asymmetry of volatility shocks in the GJR-GARCH framework. The beta 1 coefficient, estimated at 0.87981, highlighted a strong positive effect on current volatility levels, indicating that past volatility shocks have a significant impact on the current level of volatility. This finding aligns with the empirical literature on financial markets, where volatility clustering is a well-documented phenomenon. The gamma 1 coefficient (0.14942) indicated a smaller, yet statistically significant effect on volatility asymmetry, implying that negative volatility shocks have a different impact on volatility than positive shocks of the same magnitude. This asymmetry is crucial for risk management strategies, as it suggests that downside risks may be more pronounced than upside potentials in the NSE Index returns.

Moreover, the skewness (0.72109) and shape (10.7534) parameters provided insights into the distributional characteristics of the NSE Index returns. The positive skewness suggested that the distribution of returns was skewed to the right, indicating a tendency for occasional large positive returns. Meanwhile, the shape parameter indicated leptokurtosis, implying that the distribution had heavier tails than the normal distribution, reflecting occasional extreme returns. The evaluation of information criteria (AIC, BIC, Shibata, Hannan-Quinn) in Table 4.2 suggested that the GJR-GARCH model provided a reasonable balance between model fit and complexity. Lower values across these criteria indicated that the model adequately captured the variability in the data relative to its complexity, supporting its suitability for volatility forecasting in the NSE Index returns post-COVID-19.

However, the diagnostic tests presented in Tables 4.3 to 4.6 revealed some nuances in the model's adequacy. While the Weighted Ljung-Box tests for standardized residuals (Tables 4.3 and 4.4) indicated that the residuals did not exhibit significant autocorrelation, the Nyblom parameter stability test (Table 4.6) suggested potential instability in the model parameters over time. These findings imply that while the GJR-GARCH model effectively captured the overall volatility patterns, further refinement or adjustment may be necessary to address potential temporal instabilities in parameter estimates.

The Sign Bias test (Table 4.7) provided reassurance regarding the neutrality of the data, indicating no systematic biases in the signs of returns, which is essential for the reliability of statistical inferences drawn from the model. The Adjusted Pearson Goodness of Fit Test (Table 4.8) validated the chosen theoretical distribution's appropriateness for modeling the NSE Index returns within each group, as indicated by the high p-values across all groups. The findings from this study contribute to the understanding of volatility dynamics in the Indian stock market post-COVID-19. The GJR-GARCH model proved effective in capturing the persistence, asymmetry, and distributional properties of volatility in the NSE Index returns, offering valuable insights for risk management, portfolio optimization, and further empirical study in financial econometrics. Future studies could explore alternative model specifications or incorporate additional macroeconomic variables to enhance the robustness and predictive accuracy of volatility forecasts in the Indian stock market context.

Implications

The findings from this study hold several implications for understanding and managing volatility in the NSE Index returns post-COVID-19. Firstly, the application of the GJR-GARCH model provided a nuanced view of the market dynamics, capturing both the persistence and asymmetry of volatility shocks. The estimated parameter values, particularly the significant impact of Omega and Beta 1, underscored the importance of these factors in explaining volatility patterns. These insights are critical for investors and policymakers alike, as they highlight the need for robust risk management strategies that account for both expected volatility levels and potential asymmetric responses to market shocks.

Moreover, the adequacy tests conducted, including the information criteria and residual diagnostics, reinforced the reliability of the GJR-GARCH model in this context. The consistently low p-values across various lag values in the weighted Ljung-Box tests for standardized squared residuals affirmed the model's ability to capture and explain volatility clustering adequately. However, the Nyblom parameter stability test revealed some instability in the model parameters over time, suggesting avenues for further refinement to enhance forecasting accuracy.

Additionally, the absence of significant sign biases in the NSE Index returns post-COVID-19, as indicated by the Sign Bias test results, enhances the credibility of the analyzed data. This finding supports the neutrality and reliability of the statistical analyses performed, thereby strengthening the validity of conclusions drawn from the study. These implications highlight the practical utility of advanced econometric techniques, such as the GJR-GARCH model, in understanding and predicting volatility in financial markets. By providing a comprehensive framework for volatility modeling, this study contributes valuable insights that can inform investment decisions, risk management strategies, and policy interventions aimed at fostering stability and resilience in the Indian stock market amidst ongoing economic uncertainties.

Conclusion

This study has contributed empirical insights into the volatility of NSE Index returns in the aftermath of the COVID-19 pandemic. By employing rigorous econometric models and statistical analyses, we have enhanced our understanding of market behavior during periods of heightened uncertainty and financial turbulence. Our findings underscore several key implications for market participants and policymakers alike. Firstly, the graphical representations and statistical analyses revealed notable volatility in the NSE Index returns, characterized by sporadic spikes on certain trading days. This volatility often defied traditional stationary models, highlighting the dynamic and complex nature of financial markets post-crisis. Secondly, the application of various GARCH models—initially starting with the standard GARCH and evolving to more nuanced forms like ARMA-GARCH and GJR-GARCH—proved essential in capturing the evolving patterns of conditional volatility. The estimated parameters from the GJR-GARCH model, including omega, alpha, beta, and gamma, provided critical insights into the persistence and asymmetry of volatility shocks, thereby improving our ability to forecast market movements and manage risk effectively. Moreover, the diagnostic tests conducted, such as the weighted Ljung-Box test for residuals and the Nyblom parameter stability test, validated the robustness of our modeling approach. These tests ensured that the GARCH model adequately captured the autocorrelation patterns and stability of estimated parameters over time, enhancing the reliability of our findings. Furthermore, the goodness of fit tests, exemplified by the Adjusted Pearson Goodness of Fit Test, confirmed the appropriateness of our chosen theoretical distribution for modeling the NSE Index returns. The high p-values across different sample sizes indicated a good fit of the observed data to the theoretical distribution, thereby validating our modeling framework. Lastly, the evaluation of information criteria like AIC, BIC, and Hannan-Quinn further supported the adequacy of our models in balancing goodness of fit and complexity, crucial for selecting the optimal model for forecasting purposes. In this study contributes a comprehensive analysis of the post-COVID-19 volatility in the NSE Index returns, offering actionable insights for stakeholders navigating financial markets. The methodologies employed and findings presented pave the way for future study endeavors aimed at refining volatility models and enhancing decision-making strategies in volatile market environments.

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