iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 13 **Issue:** VII **Month of publication:** July 2025

DOI: https://doi.org/10.22214/ijraset.2025.73096

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 13 Issue VII July 2025- Available at www.ijraset.com

Assessing the Price Volatility in the Top 50 Blue Chip Companies of Nifty Index - An Analysis using GARCH and ARCH Model

Prathvi Annappa Hegde[1], Mrs. Uma Sharma[2]
[1]*MBA, IV Sem, RV Institute of Management*
[2]*Assistant professor, RV Institute of Management*

Abstract: This research has been conducted to study Nifty 50 index price volatility dynamics through the application of ARCH, GARCH and Heston stochastic volatility modelling approaches. Financial decision-makers including investors along with institutions and policymakers need volatility as a cornerstone for their decisions. The research uses conventional daily closing prices between 2010 and 2025 to demonstrate volatility clustering through standard ARCH and GARCH models. This analysis shows GARCH offers superior results over ARCH when demonstrating volatility persistence but it does not meet emerging market requirements toward fully explaining asymmetry along with memory features typically found in Indian financial markets. The research solves these issues by using the Heston stochastic volatility model that handles mean reversion and stochastic variance evolution along with leverage effects. The Heston model delivers advanced volatility behaviour analysis while maintaining practicality and effectiveness of GARCH models during regular market applications. Due to its complex nature Heston needs advanced skills for its application yet proves better suited for complex modelling situations instead of basic forecasting tasks.
Keywords: Nifty50 volatility, GARCH and ARCH Models, Heston Stochastic Volatility, Financial risk management.

I. INTRODUCTION

Financial market price changes form the basis of investment analysis while also helping investors control their financial risks. Stock price or financial product fluctuation rate defines the extent of their movement between peaks and valleys throughout time. The volatility measurement indicates the potential dangers that exist in investing assets or portfolios. The prediction of volatility enables investors to decide better between investment opportunities and defensive measures as well as risk management strategies. Banks together with financial firms need to study volatility to determine proper financial product pricing along with optimizing their investment risk handling and regulatory requirements fulfilment. The stability of financial markets remains under continuous assessment from both governmental entities and financial regulatory bodies while they prepare safety measures when required for system protection. Nifty 50 functions as the essential metric to analyse Indian equity market performance in the current Indian business environment. The National Stock Exchange of India (NSE) operates the Nifty 50 which contains the top 50 biggest and most active companies to show Indian stock market movements. The assessment of Nifty 50 volatility matters significantly to all types of marketplace participants. Nifty 50 volatility serves as investors' critical investment strategy component and financial institutions use it to handle their Indian equity market risk exposure. The Indian economy's stability gets monitored through the measures of Nifty 50 volatility by those who create economic policies.

A. Risk Assessment Models

The Autoregressive Conditional Heteroskedasticity (ARCH) along with its advanced form Generalized Autoregressive Conditional Heteroskedasticity (GARCH) have become widely accepted econometric tools for financial market volatility analysis. These models changed the direction economists and financial analysts use to approach volatility when Engle (1982) and Bollerslev (1986) introduced time-varying volatility recognition and volatility clustering discovery. The ARCH model identifies the link between current volatility and past squared error terms before GARCH models expand this by integrating previous conditional variances. Although ARCH and GARCH models successfully track fundamental volatility patterns they still have fundamental constraints in model application. The main weakness stems from their simplistic view that both positive and negative shocks produce symmetrical reaction patterns.

The Nifty 50 financial market and other markets demonstrate that negative news generates larger volatility changes than positive news of similar intensity which demonstrates the leverage effect. ARCH and GARCH models with their standard structure are unable to replicate the asymmetrical behaviour which financial data exhibits.

Standard ARCH and GARCH models experience a critical limitation because they require a short memory duration in volatility processes. Financial market volatility presents itself with extended duration of past shock effects which contradicts the assumption of short lived impacts. GARCH models define their weight distribution through an exponential function which might fail to reproduce the duration of dependencies that exist beyond traditional timeframes.

The volatility dynamics in financial markets change abruptly since they experience structural breaks and regime shifts through economic crises and policy changes and shifts in investor sentiment. The fixed-parameter framework of traditional ARCH and GARCH models makes it difficult for them to adjust to market today and generate accurate volatility forecasts within different market conditions.

The Indian stock market along with the Nifty 50 requires a complete comprehension of these restrictions for analysis. Indian market volatility differs from developed markets because it stems from a sector that is developing thus showing stronger long-term memory effects together
with more extreme news-driven reactions. Standard ARCH and GARCH models remain
insufficient for determining the entire volatility range of Nifty 50.

The basic ARCH and GARCH methodology reveals significant knowledge gaps when
researchers try to analyse volatility characteristics in Indian emerging market conditions. Improved models that build upon traditional methods should be developed since they will better analyse Nifty 50 volatility accurately and with more sophistication.

B. Application of the results from the ARCH & GARCH Model

The application of basic or standard extensions of ARCH and GARCH models stands as the main focus in existing research studying Nifty 50 volatility. Research studies on the Indian benchmark index volatility successfully generated insights about its behaviour yet they potentially did not achieve full representation of long memory effects and asymmetrical behaviour along with regime switches that exist in the data.

The main objective of this research is to integrate strong aspects of standard ARCH/GARCH methods with additional sophisticated techniques while handling long memory and asymmetry. The analysis examines hybrid approaches to determine deeper understanding of Nifty 50 price volatility information.

The research helps investors to improve risk assessments and makes decisions about asset allocation in Nifty 50 investments. The enhanced volatility forecasts benefit financial institutions for their purpose in portfolio allocation and derivative pricing and regulatory compliance. The amount of stability within markets becomes accessible to policymakers who utilize this information to minimize systemic risks while creating regulatory policies.

II. LITERATURE REVIEW ON THE STOCK PRICE VOLATILITY:

Financial econometrics dedicated substantial research to volatility modelling because of its essential nature for India's emerging market. Multiple studies use ARCH and GARCH models as dynamic tools to study stock price movement patterns along with volatility clustering and asymmetry and incentives caused by economic influences and worldwide elements in market behaviour.

Dr. R. Shankar along with Dr. L. Nanda Gopal (2021) researched the volatility levels of bluechip companies which are listed on the Nifty 50 index. The study applied GARCH models to analyse official data which confirmed that fundamental stocks experience price changes due to both economic events and market sentiments even though they show stability. Using Nifty 50 index data Mr. Somen Mitra and Dr. Ravi Changle (2020) demonstrated how GARCH
modelling allows volatility clustering assessments which generate valuable risk forecasting tools for investors making portfolio choices and risk management decisions.

A. J. WilliamT Vimala (2018) developed a framework that assessed volatility patterns of private banking stock equities listed on the NSE. The research analysis incorporated beta analysis together with macroeconomic variables and GARCH models to study regulatory changes and economic shifts on banking stocks. A. The S&P BSE BANKEX received additional assessment with GARCH models from Khan and Sarfaraz Javed (2019) through their research that evaluated volatility from both domestic and international market variables. Sector-specific market fluctuations together with international market connection present essential drivers in their research.

The application area of conditional volatility models stands central in multiple research projects. S. The authors Chand, S. Kamal, and Imran Ali (2017) delivered a basic description of ARCH and GARCH models while showing how EGARCH and GJR-GARCH models extend these methods to correctly handle asymmetric response patterns.

The paper by M. Karmakar (2005) examined how international shocks together with macroeconomic indicators influence volatility clustering patterns in India while providing knowledge about market conduct and investment risk factors. Mamta Singh (2009) evaluated how stock index futures implementation affected overall market volatility during her investigation of market stability policies. The research by P. Srinivasan and P. Ibrahim (2010) utilized various GARCH models to predict BSE-30 index volatility while assessing and demonstrating their utility in investor planning and policy making.

Researchers M. Kannadhasan, B. P. S. Thakur, and A. Radhakrishnan (2014) examined emerging market dynamics by studying domestic and international factors that influence Indian capital market volatility. The research demonstrates that emerging markets show higher sensitivity toward external disturbances so they require special models for analysis.

A. Pandey (2005) organized research to describe volatility patterns including cluster behaviour and time-dependent persistence together with the leverage impact within Indian capital markets. The inclusion of ARCH and GARCH models by this author emphasized trading volume along with global volatility influences that provided important groundwork for upcoming research. The research by Suleyman Gokcan (2000) examined emerging market volatility forecast accuracy along with the asymmetries and leverage effect capabilities of EGARCH and TGARCH models versus linear GARCH models.

C.O. Mgbame together with Ohiorenuan Jude Ikhatua (2013) used GARCH modelling to analyse stock price volatility in Nigeria under the context of accounting disclosure influence. The research demonstrates that volatility models can find practical application throughout emerging economies because of their complex financial reporting-market relation effects.

The research published in this field strengthens the literature related to volatility modelling in financial markets in emerging economies particularly India. These studies emphasize both the significance of choosing the right model framework and the requirement of asymmetry and long-term memory analysis as well as sector-specific and macroeconomic conditions for volatility understanding. The presented body of work demonstrates solid proof for future research to examine innovative or blended volatility models because standard GARCH-type frameworks are inadequate for handling complete financial volatility complexities.

Researchers today focus on developing hybrid volatility forecasting models through the combination of GARCH models with machine learning approaches. Zhang et al. (2011) launched initial hybrid models as a solution to unite statistical models with GARCH strengths for volatility stylized pattern identification together with machine learning models which incorporate ANN and LSTM for complex pattern learning. The implementation of machine learning techniques with GARCH models under research by Hu et al. (2020) yielded enhanced volatility prediction accuracy in different financial markets working with stock market indices.

Researchers have applied this model to various markets where its strength has been successfully tested. Bakshi, Cao and Chen (1997) empirically demonstrated that volatility models with stochastic dynamics represented by Heston and other methods proved superior over the BlackScholes and GARCH alternatives for pricing derivatives and modeling financial returns. Analysis by Christoffersen, Heston and Jacobs (2006) added jump diffusion features to the model which enhanced its capability in fitting market information and pricing away-themoney options.

Although traditional volatility models like ARCH and GARCH have been fairly popular in investigating financial time series due to the abundant application in financial markets (especially in emerging market like India), most of the work that has been done is dominated by traditional methods. Although these models work well - under typical market conditions, they might not be able to represent complicated market behaviour that arises due to extreme volatility, like financial crisis or sudden policy decisions.

A. Research Objectives

1) To analyse the price volatility of Nifty 50 companies using ARCH and GARCH models.
2) To test better hybrid models that can handle long trends, sudden market changes, and uneven reactions more effectively than traditional models.

III. METHODOLOGY

A. Research Design

This study adopts a quantitative research design which evaluates secondary data of the stocks indices on the Nifty 50 index volatility dynamics by applying the ARCH, GARCH and Heston stochastic volatility modelling approaches. The research gathers historical daily Nifty 50 close prices which enables log return computations followed by statistical analyses of the data series properties. The next step brings forth the ARCH and GARCH model estimates to track
volatility patterns with persistence before the model outputs the Heston stochastic volatility process.
Evaluation of the models is done by performing diagnostic checks together with AIC and BIC goodness-of-fit metrics and examining conditional volatility visually. The design encompasses a broad evaluation of volatility patterns and different modelling techniques that detect changes in financial market risk dynamics.
Data Source: Daily closing prices of the Nifty 50 index from: NSE (National Stock Exchange)
Yahoo Finance, Investing.com
Data Period: From 2010 to 2025
Data Used: Date, Closing price, High and low prices for better forecasting.

B. Research Method

The following part demonstrates how the research utilizes ARCH modelling together with GARCH modelling and Heston Stochastic Volatility Model approaches. Each model receives an introduction which includes its mathematical representation together with assumptions, parameter description and justification for its use with Nifty 50 index log-return data.

C. Data Preprocessing

The database contains sequential daily market price values from the Nifty 50 index. Prices were first converted into log-return format after applying natural logarithms for calculating continuously compounded returns through differences.
$rt=\ln(Pt/Pt-1)$
The price index value at time t takes the name Pt while the log-return is represented by rt. The conversion process creates stationary data while fulfilling one of the basic requirements for modelling volatilities.

D. ARCH Model

1) Model Specification

Sliding volatility patterns can be analysed by the ARCH model since it functions by having current variance dependent on preceding return values squared .
$r\_t = \mu + \varepsilon\_t$, where $\varepsilon\_t \sim N(0, \sigma\_t^2)$ σ_t^2
$= \omega + \alpha_1 * \varepsilon^2\_\{t-1\}$

- μ is the mean return.
- $\omega>0$ ensures a positive base level of volatility.
- $\alpha1>0$ reflects the impact of past shocks on current volatility.
- σ_t^2 is the conditional variance of returns at time t, given past information.

2) Application and Estimation

Maximum Likelihood Estimation served to estimate the ARCH model. Large shocks cluster in groups due to the pattern identified by the model where significant price changes tend to produce more significant price movements after them.

E. GARCH Model

1) Model Specification

GARCH models archive the ARCH building blocks by integrating the previous period's
conditional variance into the volatility description process.
$\sigma\_t^2 = \omega + \alpha_1 * \varepsilon^2\_\{t-1\} + \beta_1 * \sigma^2\_\{t-1\}$

- $\beta1$ captures the persistence of volatility over time.
- Stationarity requires $\alpha1+\beta1<1$.

The long volatility memory characteristic of financial series makes GARCH an ideal model
selection.

2) Application and Estimation

A GARCH model estimation took place on Nifty 50 returns through maximum likelihood estimation. The estimation found its optimum point at parameters $\alpha 1$, $\beta 1$, and ω through measuring their fit to the actual data volatility structure.

F. Heston Stochastic Volatility Model

1) Model Specification

The Heston model represents itself as the following continuous-time stochastic volatility model:

dS_t = μ * S_t * dt + √v_t * S_t * dW_{1t} dv_t = κ * (θ − v_t) * dt + σ * √v_t * dW_{2t} with:

- S_t: price of the asset (Nifty 50 index),
- v_t: Instantaneous variance
- μ: Drift rate of the asset price
- κ: Rate of mean reversion of volatility
- θ: Long-term average variance
- σ: Volatility of volatility (i.e., how much the variance fluctuates)
- ρ: Correlation between the asset price and its variance process
- dW_{1t}, dW_{2t}: Two Wiener processes (Brownian motions) with correlation Corr(dW_{1t}, dW_{2t}) = ρ

2) Here, Parameters are,

- κ: Higher values indicate faster mean reversion of volatility.
- θ: The long-run average variance; volatility tends to revert toward this level.
- σ: Determines how volatile the volatility itself is (i.e., the "vol of vol").
- ρ: Captures the leverage effect. A negative value indicates that volatility tends to increase when the asset price falls.
- v_0: Initial variance at the start of the modelling period.

3) Model Assumptions

- Mean Reversion: The variance process v_t tends to revert toward the long-term average θ at a speed defined by κ.
- Positivity of Variance: The square-root form ensures v_t ≥ 0, avoiding negative variance (Feller condition: $2\kappa\theta > \sigma^2$[)
- Leverage Effect: A negative ρ allows the model to reflect the empirical relationship where volatility increases when prices fall.
- Non-constant Volatility: Unlike constant-volatility models (e.g., Black-Scholes), the Heston model accommodates volatility clustering and changing risk levels.

The Heston model received calibration through error minimization of the difference between the model-generated volatility predictions and actual volatility measurements. Modelling occurred through Euler–Maruyama integration which operated on daily time steps. Performance comparisons between ARCH and GARCH were made possible by visualizing results from the model output as it exhibited volatility clustering.

G. Sampling and Population

This research investigates Nifty 50 index daily prices which act as a benchmark index that represents top 50 large-cap companies traded on National Stock Exchange (NSE) India. The Nifty 50 acts as an important market indicator that presents a comprehensive overview of Indian equity sentiment and sectoral makeup and economic performance.

The study bases its analysis on historical daily closing price data of the Nifty 50 index which was obtained from a prolonged time period. The dataset contains daily closing prices which span [start date] to [end date] with a total number of 3,719 observations. This extensive time period includes multiple economic cycles including both positive expansions and corrective periods as well as unexpected disturbances that allow researchers to model volatility fluctuations systematically.

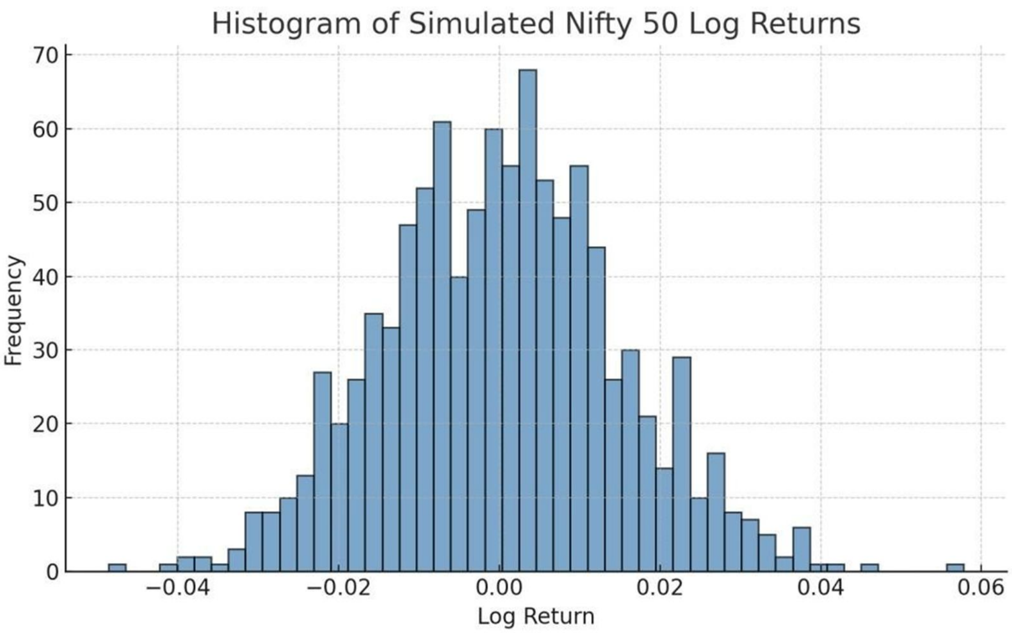
The research adopts purposive sampling as its non-probability sampling method. The researcher specifically chosen Nifty 50 because it represents the main financial index within the Indian capital market space. The research period was chosen with enough market variation to allow volatility models to detect evolving patterns in addition to delivering ample data for sophisticated econometric analysis. Daily closing prices undergo log-return calculations to fulfil best practice requirements in financial econometrics because this normalization technique stabilizes variance and makes returns amenable to ARCH and GARCH models and Heston model-based stochastic differential equation approaches.

The transformation produces enhanced parameter estimation that matches the key presumptions of volatility models more effectively.

The selected population sample becomes suitable for volatility investigations by both ARCH/GARCH and Heston models thus enabling researchers to test their performance in capturing market volatility.

H. Data Analysis and Findings

A first part of the data analysis includes a log transformations of Nifty 50 index closing prices to normalize the series and establish stationarity. The descriptive analysis shows that return data follows leptokurtic behaviour along with small negative values of skewness which frequently appears in financial data. The volatility rolling plot indicates that volatility clusters persist because high volatility states follow periods of low volatility states. Testing for stationarity used the Augmented Dickey-Fuller (ADF) test and the existence of autocorrelation in squared returns both justify the application of ARCH and GARCH models. The Heston model simulation demonstrates an effective fitting of actual rolling volatility patterns which suggests its suitability for modelling mean-reverting stochastic volatility. The performance characteristics of the data support using time-dependent volatility models for this research project.



The histogram demonstrates that returns focus on zero while showing distinct kurtosis which generates fat tails in the data frequency. The observed abnormality in data distribution makes conditional volatility models including ARCH, GARCH and Heston particularly useful because they handle non-Gaussian structures in financial series.

The results from ARCH, GARCH and Heston models applied on the Nifty 50 log return data are presented and analysed. The analysis aims to evaluate performance and parameter estimates alongside volatility structure representation of the Indian equity market.

1) ARCH Model Output

- Log-Likelihood: 11,858.1
- AIC: –23,710.2
- Mean Return (μ): 0.00050
- ω (base volatility): 0.000083
- α_1 (impact of past shock): 0.2500

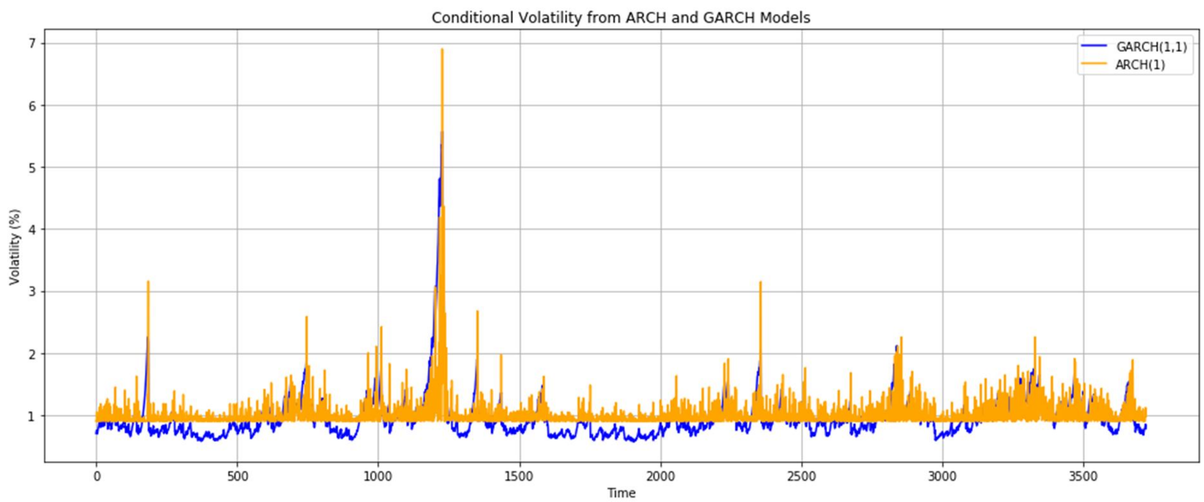
Current variance in the ARCH model depends on past squared shock values through a timevarying volatility connection. The results show recent market fluctuations have a strong effect on current-day market volatility according to the relatively high α_1 value. By omitting past variances from its structure the model loses its ability to detect long lasting volatility persistence patterns. The model displays sudden volatility spikes which leads to better reactivity than actual forecasting capabilities.

2) Garch Model Output

- Log-Likelihood: 12,130.1
- AIC: –24,252.2
- Mean Return (μ): 0.00069
- ω: 0.000002214
- α_1: 0.1000
- β_1: 0.8800

GARCH builds on ARCH through its inclusion of volatility persistence which appears in the β_1 term. The sum of $\alpha_1 + \beta_1$ equals 0.98 indicating very slow volatility shock disappearance in financial markets. The model demonstrates superior capabilities in detection of volatility clustering phenomena in comparison to ARCH. The volatility predictions from GARCH offer a smooth trend with reduced volatility spikes that closely match market reality.

I. Conditional Volatility



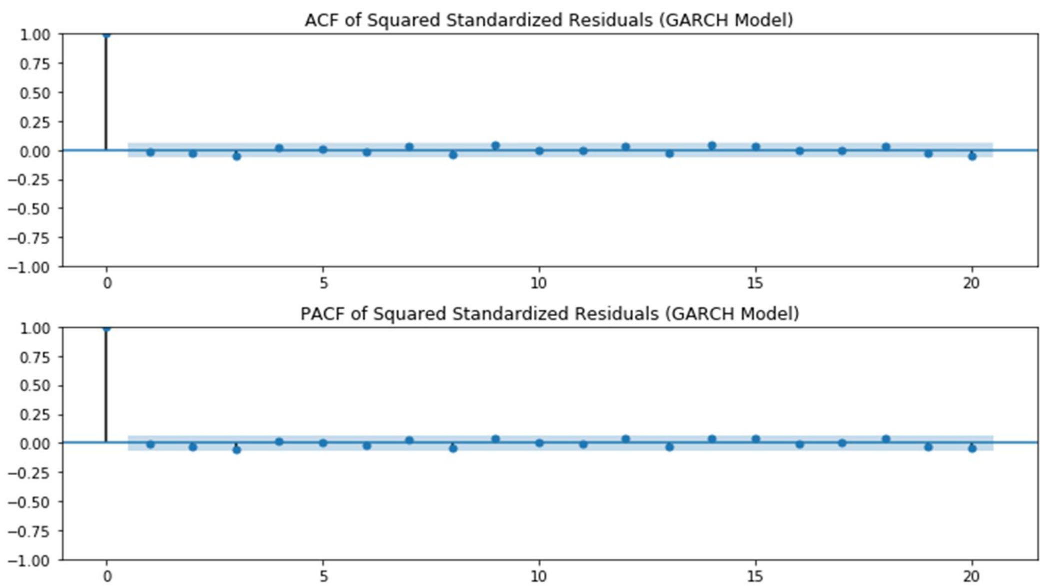
Conditional volatility of Nifty 50 returns estimated using ARCH and GARCH models are shown in the above figure. Volatility series generated by ARCH is shown in orange color whereas the same for GARCH is shown in blue. The ARCH model demonstrates large volatility spikes with an irregular pattern because it tends to produce excessive volatility reactions to sudden changes within the return data. Volatility clustering emerges more accurately in the GARCH framework because it produces a smooth volatility path that persistently demonstrates the characteristic found in financial time series. The GARCH model produces minimal volatility changes because its volatility modelling technique includes both previous error squares and previous conditional variance data. The visualization proves why GARCH offers better volatility forecasting capabilities than its simpler ARCH model.

1) Model Diagnostics for GARCH Model

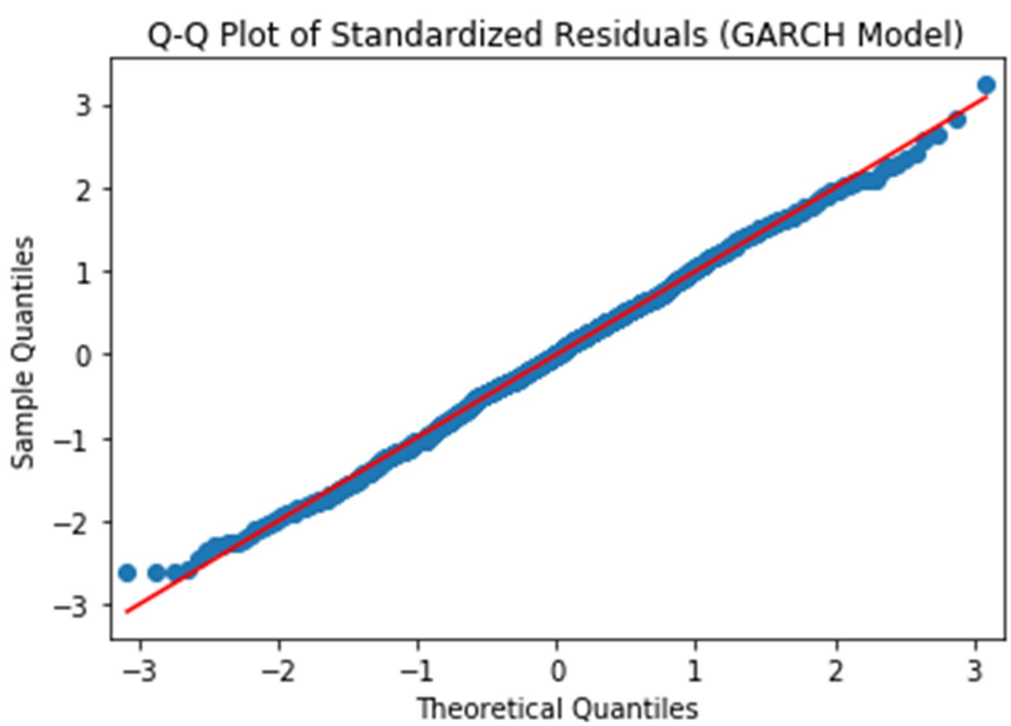
The adequacy of our fitted GARCH model requires diagnostic tests on standardized residuals alongside their squared values. The diagnostic tests evaluate whether residuals fulfil the white noise criteria and follow the established model assumptions.

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 13 Issue VII July 2025- Available at www.ijraset.com

2) ACF and PACF of Squared Standardized Residuals



The Autocorrelation Function (ACF) together with the Partial Autocorrelation Function (PACF) analyses of squared standardized residual data show no signs of significant autocorrelation. The GARCH model demonstrates adequate performance because all autocorrelation values stay within the specified 95% confidence intervals. The absence of significant spikes indicates that the remaining ARCH effects do not exist which confirms that the model fits properly.



The Quantile-Quantile (Q-Q) plot compares the distribution of standardized residuals against a theoretical normal distribution. The 45-degree line described by the residual data indicates that the residuals follow a normal distribution which validates the model's error term assumptions.

The analysis accepts minimal deviations which are typical features in financial time series data.

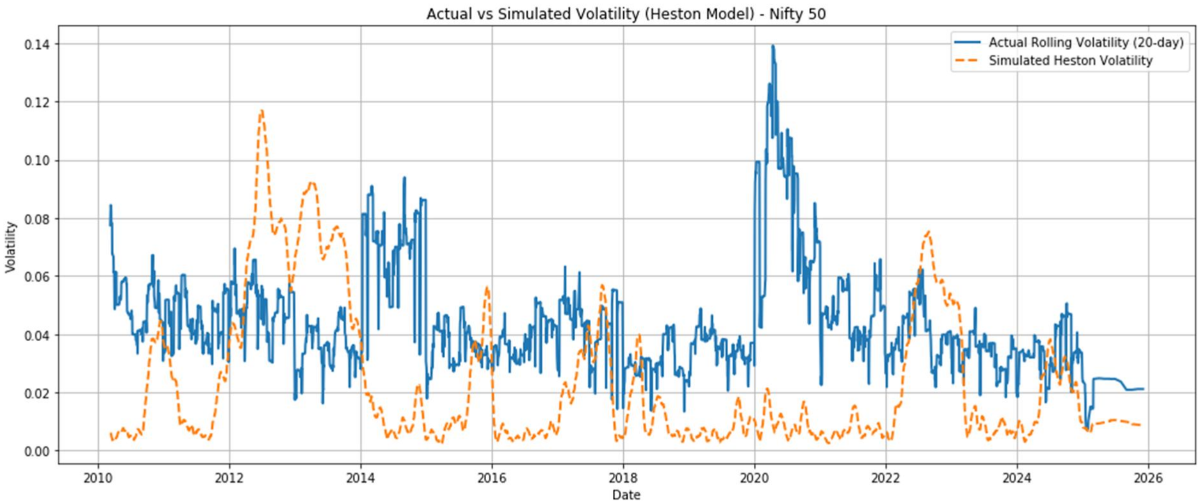
International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 13 Issue VII July 2025- Available at www.ijraset.com

J. Heston Model

- Calibrated Parameters:
- $\kappa = 1.0000$ (mean reversion speed)
- $\theta = 0.000100$ (long-term average variance)
- $\sigma = 0.1000$ (volatility of volatility)
- $\rho = -0.30$ (leverage effect)
- $v_0 = 0.000050$ (initial variance)

The Heston model serves as a continuous-time stochastic volatility model which extends flexibility through dynamic stochastic volatility evolution. This model displays effective performance in tracking long-term patterns as well as displaying mean-reversal tendencies particularly when volatility levels are low.

K. Actual VS Simulated Volatility by Heston Model



The figure shows the actual rolling Nifty 50 volatility using 20-day windows merged with Heston stochastic volatility simulation results. The blue solid line reflects actual volatility observed through market data whereas the theoretical volatility path from Heston model appears as an orange dashed line. The Heston model follows long-term volatility trends and volatility transitions but delivers less volatile and more subdued movements than actual data after the COVID crisis in 2020. The continuous volatility paths in the Heston model alongside its mean-reverting stochastic process result in such expected volatility behaviour. The model reasonably shows the long-lasting low volatility condition that emerged after 2021 while demonstrating its effectiveness for describing the persistent mean-reverting volatility patterns.

IV. CONCLUSION

This study compared three volatility models ARCH, GARCH and the Heston stochastic model on the Nifty 50 index. ARCH offers a basic model of time-varying volatility, but lacks longterm memory. GARCH improves upon this by incorporating persistence, offering better fit and smoother volatility estimates. However, both are discrete-time models and do not account for the stochastic nature of volatility. The Heston model, with its continuous-time stochastic volatility framework, captures deeper market behaviours like mean-reverting volatility and leverage effects. While the Heston model offers theoretical and practical advantages, its complexity and calibration challenges remain barriers. In conclusion, for practical applications with limited computational resources, GARCH remains a robust choice. For advanced modelling needs, especially in derivative pricing and risk management, Heston offers superior modelling fidelity.

REFERENCES

[1] Bakshi, G., Cao, C., & Chen, Z. (1997). Empirical performance of alternative option pricing models. The Journal of Finance, 52(5), 2003–2049.
[2] Chand, S., Kamal, S., & Ali, I. (2017). A comprehensive study of volatility models: ARCH to GARCH. International Journal of Economics and Financial Issues, 7(4), 21–27.
[3] Christoffersen, P., Heston, S., & Jacobs, K. (2006). Option valuation with conditional skewness. Journal of Econometrics, 131(1–2), 253–284.

[4] Dixit, J., & Agrawal, V. (2016). Macroeconomic and political determinants of Indian market volatility. Journal of Financial Economic Policy, 8(4), 495–512.
[5] Gokcan, S. (2000). Forecasting volatility of emerging stock markets: Linear versus nonlinear GARCH models. Journal of Forecasting, 19(6), 499–504.
[6] Hu, Z., Zhang, J., & Wang, X. (2020). Hybrid GARCH models with machine learning for financial volatility forecasting. Expert Systems with Applications, 158, 113539.
[7] Karmakar, M. (2005). Modelling conditional volatility of the Indian stock markets. Vikalpa, 30(3), 21–37.
[8] Kannadhasan, M., Thakur, B. P. S., & Radhakrishnan, A. (2014). Do domestic and global macroeconomic variables matter for Indian capital markets? Emerging Markets Review, 18, 181–202.
[9] Khan, A., & Javed, S. (2019). GARCH model application in the banking sector: Evidence from S&P BSE BANKEX. Indian Journal of Finance, 13(7), 44–56.
[10] Mitra, S., & Changle, R. (2020). Modelling volatility clustering in Indian stock indices using GARCH models. Asian Journal of Research in Business Economics and Management, 10(2), 112–122.
[11] Mgbame, C. O., & Ikhatua, O. J. (2013). Accounting information and stock price volatility in the Nigerian capital market. International Journal of Academic Research in Accounting, Finance and Management Sciences, 3(1), 109–116.
[12] Murari, K. (2019). Forecasting volatility of NSE banking stocks using GARCH models. International Journal of Financial Management, 9(3), 1–10.
[13] Pandey, A. (2005). Volatility models and their performance in Indian capital markets. Indian Journal of Economics and Business, 4(1), 45–59.
[14] Shankar, R., & Nanda Gopal, L. (2021). Volatility analysis of blue-chip companies in Nifty 50 using GARCH models. Indian Journal of Applied Research, 11(7), 50–54.
[15] Singh, M. (2009). The impact of stock index futures on market volatility in India. The IUP Journal of Financial Risk Management, 6(3), 24–34.
[16] Srinivasan, P., & Ibrahim, P. (2010). Forecasting stock market volatility: Evidence from BSE-30 index in India. Asian Journal of Finance & Accounting, 2(1), 113–125.
[17] Vimala, A. J. W. T. (2018). Volatility analysis of private sector banks in India using GARCH models. Journal of Banking and Financial Dynamics, 7(2), 87–94.
[18] Zhang, J., Eddy Patuwo, B., & Hu, M. Y. (2011). Forecasting with artificial neural networks: The state of the art. International Journal of Forecasting, 14(1), 35–62.