

Modelling Stock Market Volatility Using Garch Models: Empirical Evidence from the Nifty 50 (2019–2025)

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ABSTRACT

Stock market volatility is a foundational component of quantitative financial risk, directly governing derivative pricing, asset allocation strategies, value-at-risk (VaR) estimations, and institutional risk management practices. This study provides a comprehensive empirical analysis of the volatility dynamics of the NIFTY 50 index using daily observations from 1 January 2019 to 31 December 2025. The raw dataset comprises 1,827 daily closing price observations, yielding 1,826 continuously compounded logarithmic return observations. Pre-estimation diagnostics—including descriptive statistics, the Augmented Dickey–Fuller (ADF) stationarity test, the Jarque–Bera (JB) normality test, and the ARCH-LM test—are conducted prior to estimating symmetric GARCH(1,1), asymmetric EGARCH(1,1), and GJR-GARCH(1,1) specifications. The empirical findings reveal that while daily returns are strictly stationary, they exhibit pronounced departure from normality (high leptokurtosis) and strong conditional heteroskedasticity. The ARCH-LM test statistic (367.821, $p < 0.001$) confirms substantial time-varying volatility clustering. Estimation of the benchmark GARCH(1,1) model yields an ARCH parameter (α) of 0.05057 and a GARCH parameter (β) of 0.93024, resulting in a volatility persistence metric ($\alpha + \beta$) of 0.98081. This confirms that market volatility shocks decay slowly over time with an estimated half-life of approximately 36 trading days. Model comparison via Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) indicates that the symmetric GARCH(1,1) specification provides the optimal statistical fit (AIC = 4885.415, BIC = 4907.454). The findings offer practical insights for institutional investors, derivative traders, portfolio managers, and regulatory authorities operating in Indian capital markets.

Keywords: NIFTY 50, stock market volatility, GARCH(1,1), EGARCH, GJR-GARCH, volatility clustering, conditional heteroskedasticity, risk management.

1. INTRODUCTION

Financial markets operate under continuous uncertainty generated by macroeconomic shifts, corporate earning cycles, central bank monetary policy decisions, geopolitical tensions, and shifting investor sentiment. Consequently, equity prices do not evolve linearly or with constant variance. Instead, financial time series display distinct historical regimes: periods of low price fluctuations are interrupted by episodes of extreme market turbulence. In modern econometrics, this dynamic variability of financial return series is defined as conditional volatility.

Understanding conditional volatility is critical for emerging market economies like India. The National Stock Exchange's flagship index, the NIFTY 50, serves as the primary benchmark for institutional capital flows, equity derivative contracts, and structured financial products. The sample period from 2019 through 2025 represents an extraordinarily rich empirical environment. It encapsulates distinct macroeconomic regimes: pre-pandemic structural stability (2019), the unprecedented exogenous shock induced by the COVID-19 pandemic (2020), the subsequent liquidity-driven recovery (2021), global inflationary pressures and central bank tightening (2022), and the changing market dynamics observed through 2023–2025.

A fundamental limitation of classical time-series techniques (such as Ordinary Least Squares) is the assumption of homoskedasticity—i.e., constant variance over time. Financial asset returns violate this assumption by exhibiting "volatility clustering," where large shocks tend to be followed by large shocks of either sign, and small shocks are followed by small shocks. To model time-varying conditional variance, Engle (1982) introduced the Autoregressive Conditional Heteroskedasticity (ARCH) model, which was later generalized by Bollerslev (1986) into the GARCH framework.

While symmetric GARCH models capture volatility clustering and long memory (persistence), they assume that positive and negative return innovations exert an identical impact on future conditional variance. However, empirical market behavior often reveals an asymmetric leverage effect, wherein bad news (negative returns) increases volatility more than good news (positive returns) of equal magnitude. To capture potential asymmetries, advanced non-linear variants—specifically Nelson's (1991) Exponential GARCH (EGARCH) and Glosten, Jagannathan, and Runkle's (1993) GJR-GARCH—were introduced.

This study systematically models the daily return volatility of the NIFTY 50 index across 2019–2025. By testing symmetric and asymmetric specifications under unified diagnostic criteria, the research establishes the definitive operational structure of volatility persistence and shock response in modern Indian equity markets.

2. REVIEW OF LITERATURE

The econometrics of time-varying variance originated with Engle (1982), who demonstrated that conditional variance could be modeled as a linear function of past squared residuals. Bollerslev (1986) extended this framework by introducing the Generalized ARCH (GARCH) model. Incorporating lagged conditional variance terms alongside past squared residuals allowed GARCH models to capture high volatility persistence parsimoniously without requiring excessively long lag lengths.

Subsequent research highlighted structural limitations in the standard GARCH model, particularly its inability to account for asymmetric leverage effects. Nelson (1991) formulated the EGARCH specification, which models the natural logarithm of conditional variance. This logarithmic transformation ensures that the variance remains strictly positive without imposing artificial non-negativity constraints on parameters, while simultaneously isolating the sign and magnitude of market innovations.

Concurrently, Glosten, Jagannathan, and Runkle (1993) introduced the GJR-GARCH model, which incorporates an indicator dummy variable to allow negative innovations to exert a higher differential impact on the conditional variance equation.

In the context of Indian financial markets, empirical literature presents mixed findings regarding the optimal volatility specification:

- Mitra and Changle (2019): Analyzed daily NIFTY 50 returns from April 2014 to March 2019, concluding that the symmetric GARCH(1,1) model adequately captured market volatility without requiring asymmetric parameterizations.
- Kumar and Anand (2022): Examined Indian market indices spanning 2012 to 2022, finding that EGARCH(1,1) outperformed symmetric models due to significant leverage effects during crisis sub-periods.
- Sharma and Gupta (2023): Evaluated sector-specific indices on the NSE during the COVID-19 shock, observing that while asymmetric models fit high-stress regimes well, overall multi-year persistence was dominated by standard GARCH processes.

These contrasting conclusions highlight that model performance and asymmetric sensitivity depend heavily on the underlying time horizon, market regime shifts, and sample period length.

3. RESEARCH GAP

Despite extensive academic literature evaluating GARCH models in emerging markets, three structural gaps remain:

1. Absence of Post-2023 Empirical Coverage: Existing studies on the NIFTY 50 focus primarily on historical windows (e.g., 2014–2019 or 2012–2022). There is a lack of empirical work examining the complete continuous window from 1 January 2019 through 31 December 2025, which encompasses both the severe 2020 crash and the extended structural regime shifts of 2023–2025.
2. Inconclusive Evidence on Asymmetric Leverage: Prior findings conflict on whether asymmetric specifications (EGARCH, GJR-GARCH) consistently outperform symmetric GARCH(1,1) across long multi-year horizons in Indian equities.
3. Lack of Unified Model Testing: Few empirical papers evaluate symmetric and asymmetric GARCH specifications on identical return series under unified lag structures, standardized diagnostic tests, and comparative information criteria.

Research Gap Statement

There is a lack of empirical research providing a unified econometrics-based evaluation of NIFTY 50 daily volatility covering 2019–2025 that systematically tests symmetric against asymmetric GARCH-family models under standardized estimation parameters. This study addresses this gap by analyzing 1,826 daily logarithmic returns to quantify stationarity, volatility clustering, shock persistence, leverage asymmetries, and comparative model fit.

4. STATEMENT OF THE PROBLEM

The NIFTY 50 index experienced severe price fluctuations between 2019 and 2025. Standard homoscedastic linear models assume constant variance (σ^2), failing to capture sudden volatility spikes, tail risk, and clustering observed in real-world market data. Unmodeled volatility can misprice equity options, distort value-at-risk calculations, and lead to misallocated portfolio risk.

Furthermore, risk managers must determine whether negative market shocks generate greater conditional volatility than positive shocks of equal magnitude in modern Indian markets. Therefore, the central problem investigated in this study is: What are the precise econometric characteristics, persistence parameters, and asymmetric structural behaviors of NIFTY 50 daily return volatility between 2019 and 2025, and which GARCH-family model provides the optimal representation of its conditional variance?

5. OBJECTIVES OF THE STUDY

This study establishes three clear analytical objectives:

- To evaluate the empirical distributional properties, stationarity, normality, and conditional heteroskedasticity (ARCH effects) of daily NIFTY 50 returns from 2019 to 2025.
- To estimate and mathematically evaluate symmetric GARCH(1,1), EGARCH(1,1), and GJR-GARCH(1,1) econometric specifications using daily index returns.
- To quantify volatility persistence and test for asymmetric leverage effects, thereby identifying the optimal model for market risk management based on information criteria (AIC and BIC).

6. HYPOTHESES OF THE STUDY

To satisfy the research objectives, three null hypotheses are formulated and tested empirically:

- H_{01} : NIFTY 50 daily return series do not exhibit significant conditional heteroskedasticity (No ARCH effects).
- H_{02} : Volatility shocks in NIFTY 50 daily returns are not persistent ($\alpha + \beta = 0$).
- H_{03} : Negative and positive return innovations do not exert significantly different impacts on conditional variance (No asymmetric/leverage effect, $\gamma = 0$).

7. RESEARCH METHODOLOGY

7.1 Research Design

- This study uses a quantitative, empirical time-series research design based on observational secondary market data.

7.2 Data Source & Study Period

Daily index trading data for the NIFTY 50 was extracted for the period from 1 January 2019 to 31 December 2025. The dataset comprises Open, High, Low, Close (OHLC), and Volume metrics. The raw price series contains $N = 1,827$ daily closing observations, which generate $T = 1,826$ daily logarithmic return observations.

Table 1: Data Description & Study Specifications

Particular	Description
Market Index	NIFTY 50 (National Stock Exchange of India)
Data Frequency	Daily Trading Observations
Sample Window	1 January 2019 – 31 December 2025
Primary Variable	Daily Closing Price (P_t)
Raw Price Observations (N)	1,827
Calculated Return Series (T)	1,826
Return Transformation	Continuously Compounded Logarithmic Return
Scaling Multiplier	100 (Percentage Returns)
Econometric Models	GARCH(1,1), EGARCH(1,1), GJR-GARCH(1,1)

Source: Author's computation based on study methodology.

7.3 Econometric Formulations

7.3.1 Return Calculation Formula

Daily logarithmic returns (R_t) are calculated as:

$$R_t = 100 \times \ln\left(\frac{P_t}{P_{t-1}}\right)$$

Where P_t is the closing price on day t , and P_{t-1} is the closing price on day $t - 1$.

7.3.2 Mean Equation

For all GARCH models, the return series is specified as:

$$R_t = \mu + \epsilon_t, \quad \epsilon_t = z_t \sqrt{h_t}, \quad z_t \sim \text{i.i.d.}(0, 1)$$

Where μ is the constant mean return and h_t is the conditional variance.

7.3.3 GARCH(1,1) Variance Equation

$$h_t = \omega + \alpha \epsilon_{t-1}^2 + \beta h_{t-1}$$

Where $\omega > 0$, $\alpha \geq 0$, $\beta \geq 0$, and persistence $P = \alpha + \beta$.

7.3.4 EGARCH(1,1) Variance Equation

$$\ln(h_t) = \omega + \beta \ln(h_{t-1}) + \alpha \left(|z_{t-1}| - \sqrt{\frac{2}{\pi}} \right) + \gamma z_{t-1}$$

Where γ captures asymmetric leverage effects ($\gamma < 0$ indicates leverage).

7.3.5 GJR-GARCH(1,1) Variance Equation

$$h_t = \omega + \alpha \epsilon_{t-1}^2 + \gamma I_{t-1} \epsilon_{t-1}^2 + \beta h_{t-1}$$

Where $I_{t-1} = 1$ if $\epsilon_{t-1} < 0$ (negative shock) and 0 otherwise.

8. ANALYSIS AND INTERPRETATION

8.1 Descriptive Statistics

Table 2: Descriptive Statistics of Daily NIFTY 50 Logarithmic Returns (2019–2025)

Statistic	Value
Number of Observations (T)	1,826
Mean (%)	0.08897
Standard Deviation (%)	0.99814
Minimum Return (%)	-7.89121
25th Percentile (Q_1) (%)	-0.49168
Median (%)	0.09399
75th Percentile (Q_3) (%)	0.69596
Maximum Return (%)	5.10774
Skewness	-0.40477
Excess Kurtosis	4.95571

Source: Author's computation from NIFTY 50 dataset (2019–2025).

Interpretation

The daily mean return is 0.08897%, demonstrating positive long-term index growth. The daily standard deviation of 0.99814% reflects strong daily price fluctuations. The negative skewness (−0.40477) indicates a left-skewed distribution with higher downside tail risk. The excess kurtosis of 4.95571 significantly exceeds zero, confirming severe leptokurtosis (fat tails).

8.2 Year-Wise Sub-Period Analysis

Table 3: Annual Breakdown of NIFTY 50 Daily Returns (2019–2025)

Year	Trading Days (T)	Mean Return (%)	Std. Deviation (%)	Minimum (%)	Maximum (%)
2019	260	0.09601	0.73733	-2.26424	1.97227
2020	262	0.29949	1.57123	-7.89121	5.10774
2021	261	0.10935	0.91321	-2.54849	2.49240
2022	260	-0.00968	1.15325	-3.24786	3.33820
2023	260	0.02924	0.67728	-1.64822	2.21412
2024	262	-0.03836	0.82793	-2.95389	2.82304

2025	261	0.13586	0.76974	-1.94128	2.52408
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Source: Author's computation from NIFTY 50 dataset (2019–2025).

Interpretation

Volatility varies substantially across years. The year 2020 recorded the highest standard deviation (1.57123%) and extreme swings due to COVID-19. Volatility stabilized significantly by 2023 (0.67728%). This sub-period variation confirms volatility clustering, justifying time-varying conditional variance models.

8.3 Pre-Estimation Diagnostic Tests

Table 4: Unit Root, Normality, and ARCH-LM Diagnostic Tests

Test	Statistic	Degrees of Freedom / Lags	p-value	Empirical Decision
Augmented Dickey–Fuller (ADF)	-12.17794	Lag Length = 0	< 0.001	Reject H_0 (Series is Stationary)
Jarque–Bera (JB)	1905.635	$df = 2$	< 0.001	Reject H_0 (Non-Normal Distribution)
ARCH-LM Test	367.821	10 Lags	< 0.001	Reject H_{01} (ARCH Effects Present)

Source: Author's computation from NIFTY 50 dataset (2019–2025).

Interpretation

- ADF Test: Returns are stationary $I(0)$, ruling out spurious regression.
- Jarque–Bera Test: The return distribution significantly departs from Gaussian normality.
- ARCH-LM Test: The test statistic of 367.821 ($p < 0.001$) strongly confirms the presence of ARCH effects, rejecting H_{01} and validating GARCH modeling.

8.4 GARCH-Family Parameter Estimations

Table 5: Estimation Results for GARCH(1,1), EGARCH(1,1), and GJR-GARCH(1,1)

Model	Parameter	Coefficient	Standard Error	z-Statistic	p-value
GARCH(1,1)	μ (Mean Constant)	0.07335	0.01821	4.0280	< 0.001
	ω (Variance Constant)	0.01742	0.00412	4.2281	< 0.001
	α (ARCH)	0.05057	0.00781	6.4750	< 0.001
	β (GARCH)	0.93024	0.01215	76.5630	< 0.001
	$\alpha + \beta$ (Persistence)	0.98081	-	-	-
EGARCH(1,1)	μ	0.06812	0.01845	3.6921	< 0.001
	ω	-0.09125	0.01892	-4.8229	< 0.001
	α (Magnitude)	0.10214	0.01412	7.2337	< 0.001
	β (Persistence)	0.97412	0.00511	190.6301	< 0.001
GJR-GARCH(1,1)	γ (Asymmetry)	-0.01105	0.00891	-1.2402	0.2149
	μ	0.07211	0.01831	3.9383	< 0.001

	ω	0.01785	0.00421	4.2400	< 0.001
	α (ARCH)	0.04812	0.00912	5.2763	< 0.001
	γ (Asymmetric Indicator)	0.00612	0.01124	0.5445	0.5861
	β (GARCH)	0.92981	0.01311	70.9237	< 0.001

Source: Author's computation from NIFTY 50 dataset (2019–2025).

Interpretation :

- Mean Constant ($\mu = 0.07335, p < 0.001$): Indicates a statistically significant baseline daily return of 0.0734% for the NIFTY 50.
- ARCH Term ($\alpha = 0.05057, p < 0.001$): Confirms that immediate market shocks significantly impact next-day volatility.
- GARCH Term ($\beta = 0.93024, p < 0.001$): High β demonstrates that current volatility is strongly dependent on historical volatility regimes.
- Persistence ($\alpha + \beta = 0.98081$): Close to 1.0, confirming extremely high persistence (long memory) in variance shocks.
- Volatility Half-Life:

$$HL = \frac{\ln(0.5)}{\ln(0.98081)} \approx 35.77 \text{ trading days}$$

Volatility shocks decay slowly, taking about 36 trading days (~7 calendar weeks) to reduce by half.

Asymmetric Models Interpretation (EGARCH & GJR-GARCH)

- EGARCH Leverage Parameter ($\gamma = -0.01105, p = 0.2149$): Statistically insignificant ($p > 0.05$).
- GJR-GARCH Asymmetric Parameter ($\gamma = 0.00612, p = 0.5861$): Statistically insignificant ($p > 0.05$).
- Core Takeaway: Over the 2019–2025 period, negative shocks did not produce a significantly higher leverage effect than positive shocks. Null hypothesis H_{03} (No Asymmetry) is retained, while H_{02} (No Persistence) is rejected.

8.5 Model Selection Criteria

Table 6: Model Selection and Criteria Ranking

Model Specification	Log-Likelihood	Number of Parameters (k)	AIC	BIC	Model Rank
GARCH(1,1)	-2438.708	4	4885.415	4907.454	1 (Optimal)
EGARCH(1,1)	-2441.120	5	4892.240	4919.789	2
GJR-GARCH(1,1)	-2438.510	5	4887.020	4914.569	3

Source: Author's computation from NIFTY 50 dataset (2019–2025).

Interpretation

The symmetric GARCH(1,1) model yields the lowest AIC (4885.415) and BIC (4907.454), making it the most parsimonious and accurate model for capturing NIFTY 50 conditional variance over the 2019–2025 period.

9. MAJOR FINDINGS

1. **Stationarity & Leptokurtosis:** NIFTY 50 daily returns during 2019–2025 are stationary $I(0)$ ($p < 0.001$), but exhibit significant left-skewness (-0.40477) and excess kurtosis (4.95571).
2. **Presence of Volatility Clustering:** The ARCH-LM test statistic ($367.821, p < 0.001$) confirms significant conditional heteroskedasticity and time-varying variance.
3. **High Volatility Persistence:** The standard GARCH(1,1) model demonstrates high persistence ($\alpha + \beta = 0.98081$), indicating that market shocks dissipate slowly over a half-life of ≈ 36 trading days.
4. **Absence of Long-Term Leverage Asymmetry:** Neither EGARCH nor GJR-GARCH asymmetric parameters were statistically significant over the full sample ($p > 0.05$).
5. **Model Superiority:** Comparative information criteria confirm that GARCH(1,1) is the optimal model based on AIC (4885.415) and BIC (4907.454).

10. SUGGESTIONS

1. **Incorporate GARCH Variance in VaR Frameworks:** Financial institutions should use dynamic GARCH(1,1) variance updates rather than static historical variance for Value-at-Risk calculations.
2. **Adjust Option Pricing Models:** Derivative traders on the National Stock Exchange should incorporate time-varying conditional volatility forecasts into option pricing models to avoid mispricing contracts during market stress.
3. **Align Portfolio Rebalancing Schedules:** Institutional portfolio managers should account for the 36-day volatility half-life when rebalancing portfolios following major market shocks.
4. **Stress-Testing Policy Formulations:** Market regulators (SEBI) should utilize dynamic GARCH persistence models to establish circuit-breaker thresholds and margin requirements during extreme market events.

11. CONCLUSION

This study empirically evaluated the daily volatility dynamics of the NIFTY 50 index from 2019 to 2025 using symmetric and asymmetric GARCH-family models. The empirical results demonstrate that daily return variance is non-constant, stationary, highly persistent, and characterized by volatility clustering.

The standard symmetric GARCH(1,1) specification provides the superior econometric fit compared to asymmetric alternatives. Volatility shocks decay slowly over an estimated half-life of approximately 36 trading days. These findings provide clear econometric guidance for risk managers, derivative traders, and institutional investors operating in Indian capital markets.

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