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Market Volatility Across Major Nifty Sector Indices: An Empirical Study

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Abstract

This research investigates market volatility in the Indian stock market across major Nifty sector indices using empirical methods. The study examines the Nifty Bank, Nifty Pharma, Nifty FMCG, Nifty Metal, and Nifty Auto indices using annual data from Yahoo Finance for the period 2015-2025. A logarithmic transformation is applied to calculate sectoral returns, which are then examined. With the ADF test confirming that all return series are stationary, the application of volatility models is validated. This research uses the symmetric sGARCH(1,1) model to account for time-varying volatility and volatility persistence across sectors. The findings show that volatility dynamics are heterogeneous: the Banking, Pharma, and FMCG sectors exhibit greater volatility persistence, whereas the Metal and Auto sectors are more responsive to short-term market shocks. The findings highlight significant inter-sectoral linkages and limited diversification benefits during market-wide fluctuations.

Keywords: Market Volatility; Nifty Sectoral Indices; sGARCH (1,1); Return Dynamics; Indian Stock Market

1. Introduction

Financial markets are inherently characterized by uncertainty and risk, making market volatility a central concern for investors, policymakers, and researchers. Volatility reflects the degree of variation in asset prices over time and serves as a key indicator of market stability, risk perception, and investor sentiment. Understanding volatility behavior is critical in emerging markets such as India, where structural reforms, capital flows, and macroeconomic shocks significantly influence market dynamics. Sectoral indices, which represent specific segments of the economy, provide deeper insights into the transmission of risk and return patterns across different industries.

Early financial theories assumed constant variance in asset returns; however, empirical evidence consistently contradicted this assumption. Mandelbrot (1963) [11] and Fama (1965) [7] were among the first to document volatility clustering, showing that significant price changes tend to be followed by large changes. In contrast, small changes are followed by small ones. This observation laid the foundation for modern volatility modeling. Engle (1982) [6] formally introduced the Autoregressive Conditional Heteroskedasticity (ARCH) model, demonstrating that return volatility is time-varying and depends on past squared errors. Subsequently, Bollerslev (1986) [4] extended this framework with the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model, allowing volatility to rely on both past shocks and past variance, thereby capturing persistence in financial time series more effectively.

Since then, GARCH-based models have become standard tools for analyzing financial market volatility. Numerous studies have applied these models to stock indices across developed and emerging markets, confirming the presence of volatility clustering and persistence (French, Schwert, and Stambaugh, 1987; Nelson, 1991) [8, 13]. In the Indian context, volatility modeling has gained prominence due to increasing market integration, liberalization, and exposure to global financial shocks. Studies such as Batra (2004) [3] and Kumar and Maheswaran (2012) [10] document significant volatility persistence in Indian stock returns, highlighting the relevance of GARCH models in capturing market risk.

While much of the earlier literature focused on aggregate market indices, recent research emphasizes the importance of sectoral analysis. Sectoral indices reflect industry-specific fundamentals, regulatory environments, and sensitivity to macroeconomic variables. For instance, the banking sector's volatility is closely linked to interest rate movements, credit cycles, and financial stability. In contrast, the metal and automotive sectors are highly cyclical and sensitive to global commodity prices and industrial demand. Conversely, the FMCG and pharmaceutical sectors are often classified as defensive, exhibiting relatively stable performance during economic downturns. Examining volatility at the sectoral level, therefore, provides a more granular understanding of risk transmission and diversification potential.

Empirical studies have shown that volatility dynamics vary significantly across sectors. Schwert (1989) [16] emphasizes that macroeconomic uncertainty disproportionately affects cyclical industries, while Campbell *et al*. (2001) [5] highlight the growing importance of industry-specific risk over time. In emerging markets, sectoral volatility is often amplified by structural inefficiencies, policy uncertainty, and external shocks (Aggarwal, Inclan, and Leal, 1999) [1]. Studies in India, such as Sehgal and Garg (2014) [17] and Kaur (2017) [9], report asymmetric and persistent volatility across sectoral indices, reinforcing the need for sector-specific volatility modeling. Against this backdrop, the present study examines market volatility across major NSE sector indices, namely Nifty Bank, Nifty Pharma, Nifty FMCG, Nifty Metal, and Nifty Auto. These sectors collectively represent the financial, consumption-driven, defensive, and cyclical components of the Indian economy. The study employs return-based econometric techniques to examine volatility characteristics over the period 2015–2025, a decade marked by significant events including economic reforms, global trade tensions, the COVID-19 pandemic, and post-pandemic recovery. Such a period provides a comprehensive framework for assessing volatility behavior across varying market conditions.

The study employs the symmetric GARCH (1,1) model, which remains among the most widely used specifications due to its parsimonious structure and strong empirical performance. Despite the availability of advanced asymmetric models, the GARCH framework is particularly effective in capturing volatility clustering and persistence, making it suitable for comparative sectoral analysis. Prior to volatility modeling, the study conducts descriptive statistics, correlation analysis, and stationarity testing using the Augmented Dickey–Fuller test to ensure robustness and methodological validity.

This research contributes to the existing literature in three important ways. First, it provides comparative evidence on sectoral volatility dynamics within the Indian stock market. Second, it highlights differences in volatility persistence and shock sensitivity across cyclical and defensive sectors. Third, it offers practical implications for portfolio diversification, risk management, and sector rotation strategies. By focusing on major Nifty sector indices, the study enhances understanding of how market volatility manifests across industries, thereby supporting informed investment decisions and policy formulation.

2. Objectives of the study

1. To examine and compare the volatility dynamics and persistence across major Nifty sectoral indices using the sGARCH model.
2. To analyse the differential impact of market shocks on sectoral return volatility in the Indian stock market.

3. Research Methodology

3.1 Data Source and Time Span

This study employs a quantitative, empirical research design to examine market volatility across major NSE sector indices in the Indian stock market. The analysis focuses on five prominent sectoral indices, namely Nifty Bank, Nifty Pharma, Nifty FMCG, Nifty Metal, and Nifty Auto, selected due to their economic significance, varied risk profiles, and representation of cyclical and defensive sectors. The objective is to analyze volatility characteristics, persistence, and sector-specific risk dynamics. The study is based on secondary data obtained from Yahoo Finance, a widely used and reliable source of financial time-series data. Annual closing index values were obtained for the period 2015 to 2025, covering 11 years. This period encompasses different market phases, including economic expansion, slowdown, and post-pandemic recovery, thereby enhancing the robustness of the volatility assessment.

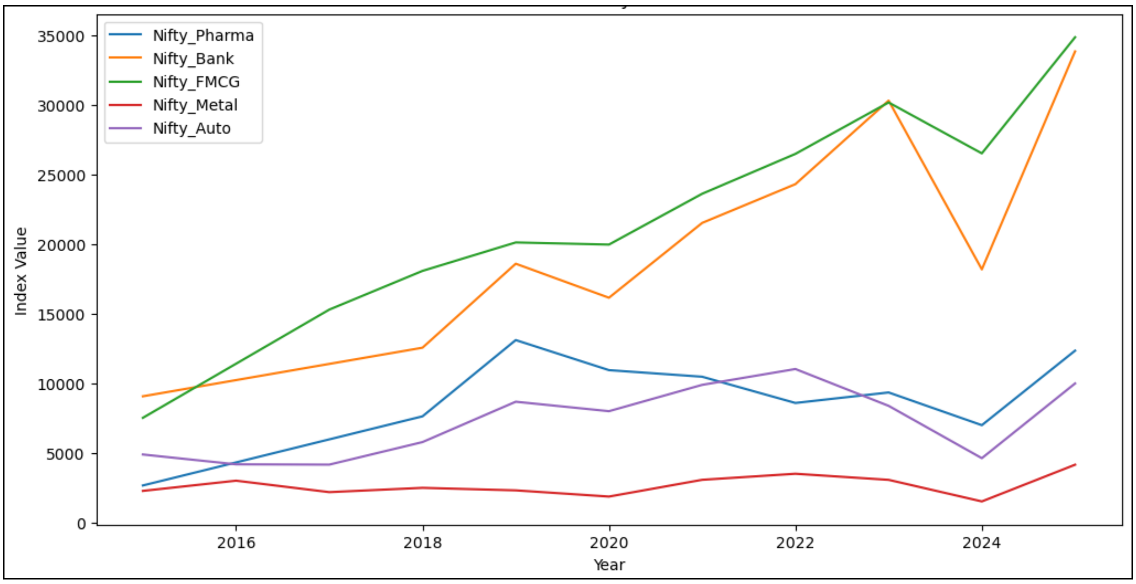

Fig 1: Actual Values of Nifty Sectoral Indices

3.2 Data Processing and Return Computation

To ensure stationarity and eliminate scale effects, index values were transformed into logarithmic returns using the following formula:

$r_t = \ln(P_t / P_{t-1})$

where;
r_t = return at time t
P_t = index value at time t
P_{t-1} = index value at time $t-1$

Log returns are preferred in financial econometrics because they stabilize variance and facilitate more accurate modeling of volatility. Initially, descriptive statistics were computed to understand the basic distributional properties and risk–return characteristics of sectoral returns. Subsequently, a correlation matrix was constructed to examine the degree of co-movement among sector indices, thereby helping to identify diversification potential and systemic linkages across sectors.

3.3 Stationarity Testing

To verify the time-series properties of the return data, the Augmented Dickey–Fuller (ADF) unit root test was applied. The null hypothesis assumes the presence of a unit root (non-stationarity). Rejection of the null hypothesis confirms stationarity, a prerequisite for volatility modeling and for valid statistical inference.

3.4 Volatility Modeling using sGARCH (1,1): To capture time-varying volatility and volatility clustering, the symmetric Generalized Autoregressive Conditional Heteroskedasticity [sGARCH (1,1)] model was employed for each sectoral index separately. The model consists of a mean equation and a conditional variance equation.

Mean Equation:
$r_t = \mu + \varepsilon_t$

Variance Equation:
$\sigma_t^2 = \omega + \alpha_1(\varepsilon_{t-1})^2 + \beta_1\sigma_{t-1}^2$

where;
σ_t^2 = conditional variance
ω = constant term
α_1 = short-run shock effect
β_1 = volatility persistence

The estimation was carried out using the Maximum Likelihood Estimation (MLE) technique under the assumption of normally distributed errors.
The sGARCH (1,1) model is widely accepted in the financial literature for its ability to capture volatility clustering, persistence, and shock transmission effectively. Applying the model separately to each sector allows comparison of volatility dynamics and identification of sector-specific risk behavior. All statistical analyses were conducted in R, using standard econometric and financial libraries to ensure computational accuracy and replicability.

4. Results and Discussion

Table 1: Descriptive Statistics of Returns of Select Nifty Sectoral Indices

	Nifty Pharma	Nifty Bank	Nifty FMCG	Nifty Metal	Nifty Auto
Mean	0.152300	0.131394	0.152973	0.059549	0.071097
Std	0.322156	0.302992	0.153619	0.464837	0.382734
Min	-0.288372	-0.510142	-0.129047	-0.691601	-0.591449
25%	-0.145651	0.099535	0.108761	-0.191240	-0.136527
50%	0.163569	0.120824	0.148525	0.028021	0.051733
75%	0.439055	0.270201	0.246788	0.239381	0.297540
Max	0.566131	0.620295	0.414971	0.991955	0.766353

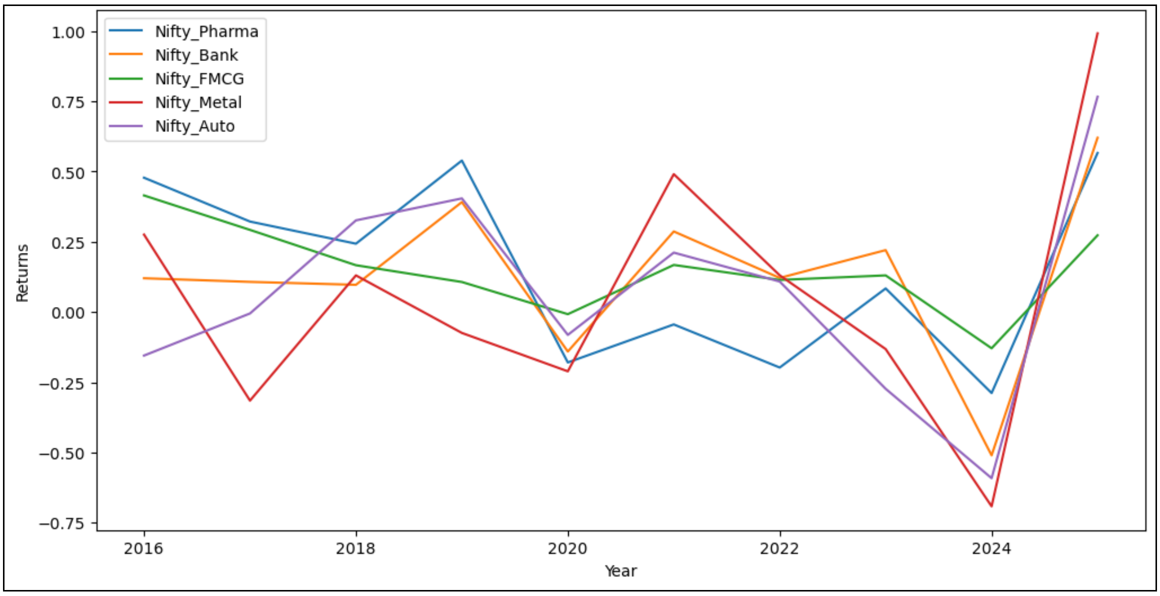

Fig 2: Log Return Series of Nifty Sectoral Indices

The table above reveals notable differences in the return behavior of selected Nifty sectoral indices. The mean returns indicate that Nifty FMCG and Nifty Pharma generated the highest average returns, reflecting their relatively stable demand conditions and defensive characteristics. In contrast, Nifty Metal and Auto show lower mean returns, suggesting cyclical performance linked to macroeconomic conditions. The standard deviation, a measure of risk, is highest for Nifty Metal, indicating substantial volatility and exposure to commodity price fluctuations. At the same time, Nifty FMCG exhibits the lowest volatility, underscoring its role as a low-risk defensive sector. The wide range between the minimum and maximum returns for the Metal and Auto sectors highlights extreme market movements and greater downside risk. Positive median values across all sectors suggest overall growth despite intermittent shocks. The upper-quartile values indicate strong upside potential, particularly in the Pharmaceutical and Banking indices. The results also confirm heterogeneous risk–return profiles across sectors, justifying volatility modeling and portfolio diversification strategies.

Table 2: Correlation Matrix of Returns of Select Nifty Sectoral Indices

Index	Nifty Pharma	Nifty Bank	Nifty FMCG	Nifty Metal	Nifty Auto
Nifty Pharma	1.000000				
Nifty Bank	0.719294	1.000000			
Nifty FMCG	0.745311	0.633393	1.000000		
Nifty Metal	0.498199	0.812566	0.601762	1.000000	
Nifty Auto	0.611650	0.842627	0.418759	0.792829	1.000000

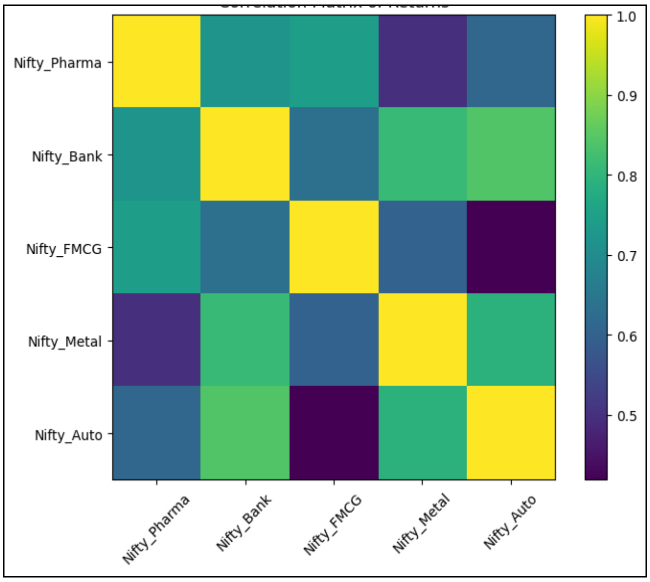

Fig 3: Correlation Matrix of Returns

A substantial degree of co movement among select Nifty sectoral index returns is evident in the figure above, indicating significant interdependence within the Indian equity market. Nifty Bank exhibits a strong positive correlation with Nifty Auto (0.8426) and Nifty Metal (0.8126), reflecting the banking sector's sensitivity to cyclical industries, driven by credit demand and economic growth. The strong association between Pharma and FMCG (0.7453) highlights their defensive nature and similar responses to consumption-led demand and macroeconomic stability. Moderate correlations between Metal and FMCG suggest partial diversification benefits. However, the generally high positive correlations across sectors imply limited risk reduction through sectoral diversification during market-wide shocks, as systematic risk dominates idiosyncratic movements. The absence of negative correlations indicates that sectoral returns tend to move in the same direction, particularly during expansionary and contractionary phases. The findings underscore the presence of contagion effects and volatility spillovers, thereby justifying the use of multivariate models, such as VAR and GARCH, to capture dynamic linkages and the transmission of shocks across sectors.

Table 3: Augmented Dickey–Fuller (ADF) Test Results for Nifty Sectoral Index Returns

Index	ADF Statistic	p-value
Nifty Pharma	-2.6358	0.0086
Nifty Bank	2.3416	0.0100
Nifty FMCG	-10.5664	0.0000^{***}
Nifty Metal	-2.9715	0.0038
Nifty Auto	-2.7097	0.0072

The ADF unit root test results provide strong evidence regarding the time-series properties of the Nifty sectoral index return series. The reported ADF statistics and corresponding p-values indicate that all sectoral returns are stationary at levels, as the null hypothesis of a unit root is rejected at the 5 percent significance level. Nifty FMCG exhibits a highly significant ADF statistic, indicating strong mean-reverting behavior and relatively stable return dynamics, consistent with its defensive-sector characteristics. The stationarity of Nifty Bank, Pharma, Metal, and Auto returns implies that shocks to returns are transitory rather than persistent and that the series revert to their long-run means over time. These findings justify applying a volatility model, such as GARCH, to examine dynamic interrelationships and volatility transmission across sectors.

5. Estimated results of sGARCH (1,1) Models

Nifty Bank Index

$r_t = 10.0105 + \varepsilon_t$

$\sigma_t^2 = 413.1120 + 0.2342(\varepsilon_{t-1})^2 + 0.3564\sigma_{t-1}^2$

Nifty Pharma Index

$r_t = 15.6588 + \varepsilon_t$

$\sigma_t^2 = 280.2072 + 0.0000(\varepsilon_{t-1})^2 + 0.7239\sigma_{t-1}^2$

Nifty FMCG Index

$r_t = 15.1049 + \varepsilon_t$

$\sigma_t^2 = 106.1850 + 0.0000(\varepsilon_{t-1})^2 + 0.4418\sigma_{t-1}^2$

Nifty Metal Index

$r_t = 3.1525 + \varepsilon_t$

$\sigma_t^2 = 972.3478 + 0.6674(\varepsilon_{t-1})^2 + 0.0000\sigma_{t-1}^2$

Nifty Auto Index

$r_t = 8.0237 + \varepsilon_t$

$\sigma_t^2 = 659.1054 + 0.6586(\varepsilon_{t-1})^2 + 0.0000\sigma_{t-1}^2$

The estimated sGARCH(1,1) results provide critical insights into market volatility across major Nifty sector indices, highlighting sector-specific volatility dynamics within the Indian equity market. The Nifty Bank index exhibits both ARCH and GARCH effects, indicating that volatility is influenced by past market shocks and volatility persistence, consistent with the banking sector's exposure to credit cycles, interest rate movements, and macroeconomic uncertainty. In contrast, the Nifty Pharma and FMCG indices exhibit dominant GARCH components with negligible ARCH effects, indicating high volatility persistence and lower sensitivity to short-term shocks, consistent with their defensive and demand-inelastic nature. The Nifty Metal and Auto indices exhibit strong ARCH effects with insignificant GARCH terms, implying that volatility is primarily driven by immediate market innovations rather than long-term persistence, consistent with their cyclical behavior and sensitivity to commodity prices, industrial demand, and economic fluctuations. The relatively higher omega values across sectors confirm the presence of baseline volatility in the market. The results demonstrate heterogeneous volatility structures across industries, thereby reinforcing asymmetric risk profiles.

6. Conclusion

This empirical study examined market volatility across major Nifty sector indices using return-based econometric techniques. The findings reveal that volatility behavior in the Indian stock market is heterogeneous and sector-specific. The distinct risk–return profiles: FMCG and Pharma display relatively stable returns, whereas the Metal and Auto sectors exhibit higher volatility and extreme fluctuations. The strong interdependence among sectors suggests limited diversification benefits during periods of market-wide stress. The ADF test confirms stationarity of all sectoral return series, validating the application of advanced time-series models. The sGARCH (1,1) results indicate volatility clustering and persistence, particularly in the Banking, Pharma, and FMCG sectors, whereas the Metal and Auto sectors show greater sensitivity to short-term shocks. Hence, the study confirms that both sector-specific fundamentals and broader macroeconomic conditions drive market volatility in India.

Despite its contributions, the study is subject to certain limitations. First, the analysis is based on annual data with a limited number of observations, which may restrict the statistical power of volatility estimates. Second, the study employs a symmetric GARCH(1,1) model, which does not capture potential asymmetries or leverage effects arising from adverse market shocks. Third, the assumption of normally distributed errors may not fully reflect the heavy-tailed nature of financial return distributions. Fourth, the study focuses only on five sectoral indices, excluding other relevant sectors such as IT, Energy, and Realty. Lastly, external macroeconomic variables such as inflation, interest rates, and global market indicators are not incorporated, which could further elucidate the mechanisms of volatility transmission.

7. Relevance of the study

The study is of significant relevance to investors, portfolio managers, policymakers, and researchers. By identifying sector-specific volatility patterns, the findings assist investors in risk assessment, asset allocation, and portfolio diversification. Policymakers and regulators can use these insights to monitor systemic risk and sectoral vulnerabilities in the Indian equity market. For academics and researchers, the study provides empirical evidence on volatility dynamics in emerging markets and offers a methodological framework for further extensions using asymmetric or multivariate models. The research enhances understanding of sectoral market behavior and supports informed financial decision-making in a volatile economic environment.

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