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Research paper

Investigating Volatility Persistence and Leverage Effect in Sectoral Indices of NSE: An Evaluation Using GARCH Models

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Abstract

Investors in the stock market always try to maximise their profit with a minimum risk. Identifying volatility in the stock market will help investors reduce their risk and create a healthy portfolio. A detailed analysis of volatility in the sectoral indices directs investors to the sector's strengths and weaknesses.
This study aims to investigate volatility in sectoral indices of the NSE using GARCH (1,1), GARCH in Mean, and EGARCH Models. Daily closing prices of 11 major sectoral indices, spanning from January 1, 2014, to June 30, 2025, are used for this study. The presence of the ARCH effect with the returns is proved for all sectoral indices using the ARCH-LM test. Our results proved that volatility persistence is present in all sectoral indices. The GARCH-in-Mean model suggests that the increased volatility in the Metal industry and the Nifty PSU Bank sector has the potential to generate high returns. The EGARCH model confirms that the leverage effect is present in all sectoral indices, indicating that bad news has a greater impact on volatility than positive news.

Keywords: *GARCH Models; Sectoral indices; Volatility; Volatility Persistence; Volatility Asymmetry; Leverage Effect.*

1. Introduction

Stock market investments are always intended to earn a profit from their holdings. Their primary objective is to maximise profit with minimal risk, and they have consistently employed various strategies to achieve this goal. The availability of adequate information about the market conditions creates opportunities for investors to diversify their portfolios by including sectoral markets, considering their risk-taking nature. Irrational trading in the stock market makes the market volatile, which increases risk in stock trading (Black, 1986; Summers, 1986; De Long et al., 1989; Shleifer & Summers, 1990). Volatility refers to the variation in returns, and higher volatility in the stock market increases the risk in stock trading. Volatility has a positive and negative impact on the market. An increase in volatility in the stock market may result in higher expected profit based on the assumption that risk is rewarded in the market (Poon & Taylor, 1992). However, in a volatile market, due to uncertainty in price fluctuations, normal investors receive fewer returns than the average return they expected, which lowers their confidence in trading (Connolly et al., 2005; Baker & Wurgler, 2007). Identifying volatility and the leverage effect in the stock market will help investors reduce their risk and create a healthy portfolio. Ignorance of volatility or the presence of volatility persistence can lead to significant losses.
Diversifying a portfolio is one of the most effective methods to mitigate investment risk. Investors can diversify their portfolios by closely observing stock market indices. Most of the existing literature focused on volatility in the stock market (Padhi, 2006; Karmakar, 2007; Kumar & Maheswaran, 2012; Vevek et al., 2022), and few studies have been conducted on selected sectoral indices of NSE (Debasish,2002; Mallikarjuna & Rao, 2017; Sing & Kumar,2020; Khera et al., 2022). A detailed analysis of volatility persistence and leverage effect in the market sectoral indices helps investors focus on the most profitable sectors and eliminate unprofitable sectoral stocks from their portfolios. This study aims to investigate the persistence of volatility and the leverage effect in sectoral indices of the NSE. This study also helps identify the risk-return relationship in sectoral index returns, enabling investors to make informed investment decisions.
Various studies on stock market volatility are available, focusing on constant variance in time series stock price data (Fama, 1965; Shiller et al., 1981). Stock market imperfections and crashes due to irrational trading (Black, 1986) are the focal points that highlight the importance of investigating volatility in the stock market. Generalised Autoregressive Conditional Heteroscedasticity models (Bollerslev, 1986) are popular models for analysing stock price volatility. GARCH models examine residuals to capture volatility in time series data.
This study employs GARCH (1,1), GARCH-in-Mean, and EGARCH models to examine volatility persistence and the leverage effect in the returns of 11 major sectoral indices on the NSE. This study aims to educate investors on the importance of paying attention to volatility, the leverage effect, price fluctuations, and the potential for higher returns when investing in stock markets. This study aims to assist

investors and professional financial advisors in distinguishing between profitable and unprofitable sectors in the market, enabling better decision-making.
The results of all the GARCH models reveal that volatility is persistent in the returns of all these 11 sectoral indices. The GARCH-in-Mean model gives significant results for the Metal industry and the Nity PSU Bank sector, indicating that volatility in these sectors is associated with higher returns. This result confirms that taking higher risks in these sectors results in higher returns. The EGARCH model results confirm that volatility asymmetry, also known as the leverage effect, is present in all these sectors, indicating that negative news has a greater impact on volatility than positive news. These results will help the investors to make better decisions by analysing the risk-return relationship and the leverage effect.
The remaining paper is organised as follows: Section 2 presents a literature review. Further, Section 3 describes the data and methodology. Section 4 details the analysis and interpretation. Section 5 presents the conclusions, and Section 6 outlines the policy implications and further scope.

2. Review of Literature

Various research studies have been undertaken occasionally to investigate and determine the impact of volatility in the stock market. The GARCH model is a popular model used for analysing volatility. Some of the research studies that served as a source of inspiration for the current study are discussed below:
Traditional theories in the field of finance state that the stock market is an efficient market in which all investors are rational, and all the information is freely available and easily discounted in the market, so that the price reflects all the available information. Therefore, it is challenging for investors to outperform the market (Fama, 1970). Classical theories assume that investors make decisions after conducting a detailed fundamental analysis, ignoring the emotional and psychological factors that affect an investor's decision-making (Fama, 1970). However, anomalies like Black Monday on October 19, 1987, broke the belief in the existence of an efficient market and confirmed the persistence of huge stock market volatility, which can result in huge losses for investors (Choudhry, 1996). Also, anomalies like the January effect, day-of-week effect, and Market bubbles give strong evidence of irrational trading that results in huge fluctuations in the stock market by indicating the weakness of EMH (French, 1980; Kumar & Jawa, 2017). Researchers believed that investors' decision-making is based on emotions and biases rather than rational thinking, which creates enormous market volatility. (Summers, 1986; De Long et al., 1989; Shleifer & Summers, 1990). Impulse decisions made by investors based on noise create inefficiency in the market, thereby reducing the profitability of investments (Black, 1986). Investors make decisions based on sentiments and biases, leading to irrational decision-making and overreactions that result in significant fluctuations in an asset's fundamental value. This leads to mispricing and volatility (Summers, 1986; De Long et al., 1989; Shleifer & Summers, 1990; Lee et al., 1991). A rise in stock market volatility can yield higher expected profits, reflecting the theory that risk is rewarded in the market (Poon & Taylor, 1992). But, in a huge, volatile market, investors receive only a few returns due to uncertainty in price fluctuations or due to the crisis prevailing in the market or due to the noise or due to irrational or sentiment factors, which lowers their confidence in trading (Connolly et al., 2005; Baker & Wurgler, 2007; Mu, 2025).
The recent studies on volatility in the stock markets revealed strong volatility persistence with leverage effect, indicating that negative news in the stock market significantly affects the stock market than the positive news (Verma & Verma, 2007; Bae et al., 2006; Alberg et al., 2008; Khan et al., 2024; Yang, 2025; Adegboyo & Sarwar,2025). Literature on Indian stock market volatility has also confirmed significant volatility persistence and a leverage effect that affects investment returns (Padhi, 2006; Kumari & Mahakud, 2015; Singh & Tripathi, 2016; Vasudevan & Vetrivel, 2016; Dungore & Patel, 2020).
A detailed analysis of the volatility of sectoral indices helps investors understand volatility persistence and identify sectors or industries where they can earn the maximum profit by taking on high risk (Khera et al., 2022). The existing literature explains that volatility is persistent in sectoral indices, which can affect investor returns (Babu & Hariharan, 2014; Khera et al., 2022; Kumar & Sharma, 2025). Researchers found a significant asymmetric effect in the sectoral indices, which confirms that the leverage effect is present in this market which indicating that negative news contributes to huge volatility (Sen et al., 2021; Mallikarjuna & Rao, 2017; Sudhakar &Viswanadh, 2018; Kumar & Sharma,2025)
Various studies use GARCH models to predict the volatility of stock market returns, but the concentration towards Sectoral indices in the Indian Stock Market is very low. To bridge this gap, this study employs GARCH models to evaluate the presence of volatility persistence, the risk-return relation, and the leverage effect in sectoral indices of the NSE.

3. Data and Methodology

3.1. Data

This study focuses on the persistence of volatility and the leverage effect in sectoral indices. For this purpose, daily closing prices of 11 major sectoral indices in the NSE are collected for analysis. The sample of data spanned over a period ranging from 1st January 2014 to 30th June 2025. The indices covered in the study are Nifty Auto, Nifty Bank, Nifty Financial Services, Nifty FMCG, Nifty IT, Nifty Media, Nifty Metal, Nifty Pharma, Nifty Private Bank, Nifty PSU Bank, and Nifty Realty.
All the required information on these indices was collected from the NSE website. Daily returns are calculated as $R_t = Ln\left(\frac{P_t}{P_{t-1}}\right)$
Where P_t is the closing price at time t, R_t is the return at time t, and P_{t-1} is the lagged value of the closing price at time t. All the data are transformed into a natural log to prevent non-stationarity issues in the analysis.

3.2. Methodology

Two symmetrical models, viz. GARCH (1,1) and GARCH-in-Mean models, and the Asymmetric model EGARCH have been applied in this study. Details of the models are given below:

3.2.1. GARCH models

The most popular time-series model in the finance literature is the Autoregressive Conditional Heteroskedasticity (ARCH) model developed by Engle (1982). The ARCH model explains that the variance of residuals at time t depends on the squared error terms from past periods. The GARCH model is termed an extension of the ARCH model. To capture the ARCH effect, Engle suggested:

$$\sigma_t^2 = \lambda_0 + \lambda_1 u_{t-1}^2 + \lambda_2 u_{t-2}^2 + \lambda_3 u_{t-3}^2 + \cdots + \lambda_q u_{t-q}^2$$

We assume that λ_i is positive because variance can not be negative, and $0 \leq \lambda_1 \leq 1$.

3.2.2. GARCH (1,1) model

The GARCH model was developed by Bollerslev (1986). This model allows the conditional variance to be dependent upon its own previous lags, so that the conditional variance equation can be stated as:

$$h_t = \lambda_0 + \lambda_1 u_{t-1}^2 + \lambda_2 h_{t-1}$$

In this model, he explained that the conditional variance at time period t (h_t) It does not only depend on the lagged square term at the previous period (U_{t-1}^2) but also the lagged variance term (h_{t-1}). This is also called the GARCH (1,1) model. λ_1 Is the ARCH term, and λ_2 Is the GARCH term.
The sum of $\lambda_1 + \lambda_2$ Must be less than 1. It shows how the changes in volatility with delayed shocks (U_{t-1}^2) and the momentum existing within the structure (h_{t-1})The GARCH term uses fewer parameters and fewer degrees of freedom and gives better estimates.

3.2.3. GARCH-in-mean (GARCH-M) model

Engle, Lilien, and Robin developed the GARCH-in-Mean model, where the conditional variance of asset returns is incorporated into the conditional mean equation. It checks whether the average mean return depends on variance (Engle et al., 1987).

$$Y_t = \propto + \beta h_t + u_t$$

$$h_t = \lambda_0 + \lambda_1 u_{t-1}^2 + \lambda_2 h_{t-1}$$

β The risk premium criterion is the risk premium coefficient, and if this coefficient is significant and positive, then a high expected return is expected to be generated by taking on a higher level of risk.
These are two symmetric models in the GARCH family, which means that positive and negative shocks experience the same kind of responses from the market.

3.2.4. EGARCH

Nelson proposed the Exponential GARCH model, which captures asymmetric effects between positive and negative returns. An asymmetric effect means negative shocks have a bigger impact on volatility than positive shocks. This model is based on the formula:(Nelson,1991)

$$h_t = \lambda_0 + \lambda_1 \frac{|U_{t-1}|}{\sqrt{h_{t-1}}} - \sqrt{\frac{2}{\pi}} + \lambda_2\, ln\,(h_{t-1}) + \delta \frac{u_{t-1}}{\sqrt{h_{t-1}}}$$

Whereas λ_1 represents the magnitude effect and λ_2 Represents the persistence of conditional volatility. δ This is the asymmetric coefficient.

4. Analysis and Interpretation

Daily closing prices of 11 NSE sectoral indices are used for the analysis. Data collected are analysed using EViews Software. Daily closing prices are converted into returns by taking the log differences of closing prices.

4.1. Descriptive statistics

Plotting the variable's data series is the first step in time series analysis. Figure 1 represents the time series plot of the return series of all indices. Time plots show that volatility clustering is present in these return series.
Table 1 presents descriptive statistics of the returns of all sectoral indices. Descriptive statistical analysis indicates that Nifty Financial Services has the highest average return (0.000614), while Nifty Media has the lowest average return (- 0.000008). The Nifty Public Sector Bank index exhibits the highest standard deviation (0.020868), indicating higher volatility, while the Nifty FMCG index shows the lowest standard deviation (0.010287), indicating lower volatility. All ten sectoral indices, except the Nifty Public Sector Banks, are negatively skewed or on the left side of the distribution. The kurtosis values of the returns for all sectoral indices are greater than 3, indicating that all return series exhibit leptokurtic distributions. The Jarque-Bera (J-B) test is used to determine whether the data are normally distributed, based on the null hypothesis that the series is normally distributed. This hypothesis is rejected for all indices at a 5% significance level. This test result confirms that these data are not normally distributed.
Figure 1 illustrates the time series plot of returns for 11 sectoral indices, viz. Nifty Auto, Nifty Bank, Nifty Financial Services, Nifty FMCG, Nifty IT, Nifty Media, Nifty Metal, Nifty Pharma, Nifty Private Bank, Nifty PSU Bank, and Nifty Realty indices. These graphs illustrate the distinct performance trajectories across industries, reflecting regulatory exposures, structural growth drivers, and other factors. When compared to broader market indices, sectoral indices show overperformances and underperformances due to these factors. During the

COVID-19 pandemic in 2020, the graphs of all the indices show significant fluctuations, indicating that sudden economic changes, lockdowns, and uncertainty caused strong market reactions, with all sectors experiencing sharp ups and downs. These graphs illustrate the presence of volatility across all sectoral indices.

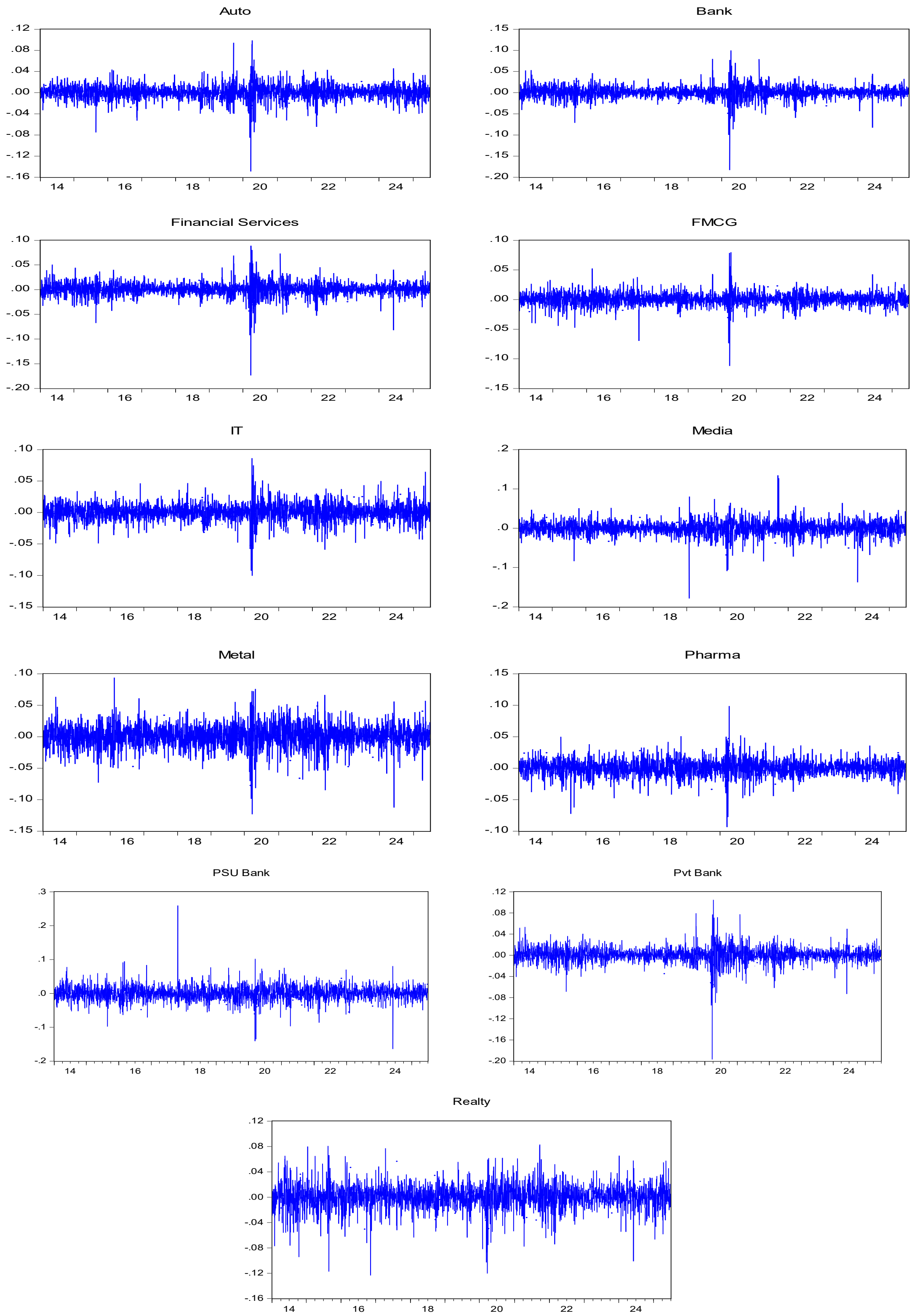

Fig. 1: Time plot of Returns of Sectoral Indices

Table 1: Descriptive Statistics

Index	Mean	Max	Min	SD	Skewness	Kurtosis	J -B (p)	N
Nifty Auto	0.00053	0.0990	-0.1491	0.01356	-0.55975	13.0036	12003.0 (0.0000)	2843
Nifty Bank	0.000568	0.1000	-0.1831	0.013946	-0.99311	19.4452	32503.6 (0.0000)	2843
Nifty Financial Services	0.000614	0.0891	-0.1736	0.013364	-1.09097	19.1369	31410.3 (0.0000)	2843
Nifty FMCG	0.000411	0.0799	-0.1120	0.010287	-0.40898	13.7355	13731.7 (0.0000)	2843
Nifty IT	0.000498	0.0864	-0.1007	0.013004	-0.35197	8.42530	3545.38 (0.0000)	2843
Nifty Media	-0.000008	0.1345	-0.1788	0.01716	-0.6416	13.0410	12138.2 (0.0000)	2843
Nifty Metal	0.000472	0.0939	-0.1233	0.01782	-0.5065	6.52523	1593.68 (0.0000)	2843
Nifty pharma	0.000371	0.0987	-0.0935	0.012265	-0.17397	7.87183	2825.92 (0.0000)	2843

Nifty PSU Bank	0.000362	0.2595	-0.1641	0.020868	0.35674	15.0542	17272.7 (0.0000)	2843
Nifty Private Bank	0.000559	0.1049	-0.1970	0.014111	-1.12438	22.5647	45942.2 (0.0000)	2843
Nifty Realty	0.000581	0.0830	-0.1234	0.019412	-0.56213	6.84760	1903.38 (0.0000)	2843

Source: Computed Data.

4.2. Testing of stationarity

A unit root test is done to determine whether the data is stationary. A time series is said to be stationary when its statistical properties, such as mean, variance, etc., remain constant over time. The Augmented Dickey-Fuller Test (ADF), developed by David Dickey and Wayne Fuller, is used to determine whether a data series contains a unit root. The null hypothesis used for the ADF test is the presence of unit roots in returns, which implies the data is non-stationary. If the p-value of the ADF test is less than 5%, then the data becomes stationary.
The results of the ADF test show that returns of all sectoral indices show a p-value of less than 5%, which indicates that the null hypothesis that "the data series has a unit root" can be rejected. These results proved that returns of all sectoral indices are stationary. Table 2 states the results of the ADF test on all indices.

Table 2: Results of Unit Root Test

Variables	t- statistic	P value
Nifty Auto	-51.63715	0.0001
Nifty Bank	-51.63246	0.0001
Nifty Financial Services	-22.28002	0.0000
Nifty FMCG	-54.13539	0.0001
Nifty IT	-53.68174	0.0001
Nifty Media	-52.92602	0.0001
Nifty Metal	-53.55043	0.0001
Nifty pharma	-51.56952	0.0001
Nifty PSU Bank	-52.51319	0.0001
Nifty Private Bank	-51.25785	0.0001
Nifty Realty	-49.34131	0.0001

Source: Computed Data.

4.3. ARCH-LM test

To check the volatility, it is necessary to do an Autoregressive Conditional Heteroscedasticity-Lagrange Multiplier (ARCH-LM) test (1982). This test checks whether the return data has an ARCH effect. The null hypothesis of this test indicates that the data have no ARCH effect. If the p-value is less than 0.05, then the null hypothesis will be rejected, and thus it will be proven that the data have an ARCH effect. If the ARCH-LM test indicates the presence of an ARCH effect in returns, then GARCH models can be employed to model volatility.
The results of the ARCH-LM test indicate that all 11 sectoral indices have a p-value of less than 0.05, suggesting that the returns of all indices exhibit an ARCH effect. So, applying GARCH models to the returns of all these sectoral indices is possible. Table 3 shows the results of the ARCH-LM Test.

Table 3: Results of the ARCH-LM Test

Variables	LM Statistics	P value
Nifty Auto	32.21015	0.0000
Nifty Bank	25.41341	0.0003
Nifty Financial Services	39.51281	0.0000
Nifty FMCG	169.2682	0.0000
Nifty IT	193.3156	0.0000
Nifty Media	34.70196	0.0000
Nifty Metal	93.22377	0.0000
Nifty pharma	105.6576	0.0000
Nifty PSU Bank	16.75813	0.0000
Nifty Private Bank	17.30519	0.0000
Nifty Realty	31.04626	0.0000

Source: Computed Data.

4.4. Analysis of volatility persistence and risk-return relationship

GARCH (1,1) and GARCH in Mean models capture volatility persistence and the risk-return relationship in sectoral indices. Since the ARCH effect is present in the returns of all 11 sectoral indices, the GARCH models can be applied to all these indices. Table 4 presents the results of the GARCH (1,1) analysis.
Results show that values of the ARCH and GARCH effects (λ_1 and λ_2)show that all sectoral indices are positive and significant, indicating that the present day's variance or shock has an impact on the prediction of future variances in returns. The significant positive value of ambdafλ_1 and λ_2 indicates that past residuals or past conditional variances of sectoral index returns are sufficient to explain and predict the persistence of volatility in returns. The basic assumption states that the sum of the ARCH and GARCH coefficients should be ≤ 1. When the sum of the values of these persistence coefficients is close to 1, it means that a high degree of volatility is persistent in the returns of all sectoral indices. The sum of these values for all 11 sectoral indices is close to 1, indicating that these data exhibit higher volatility persistence. Analysis shows that, in the GARCH (1,1) model, volatility persistence is highest for the Nifty Bank index, followed by the Nifty Auto index, and lowest for the Nifty Realty index.
The GARCH-in-Mean model (GARCH-M) helps establish a relationship between anticipated risk and expected return. The GARCH term in the mean equation represents a time-varying risk premium used to explain the returns of an index. Table 5 represents the results of the GARCH-in-Mean analysis.
λ_1 and λ_2 The values of all sectoral indices are positive and significant, which means that past residuals and past conditional variances of sectoral indices can explain and predict volatility persistence and the influence of today's variance on future variance forecasting. The persistent coefficient values of $\lambda_1 + \lambda_2$ for all sectoral indices are close to 1, indicating that returns exhibit a high degree of volatility

persistence. GARCH-in-Mean analysis reveals that volatility persistence is highest in the Nifty Bank index, followed by the Nifty Private Bank index, and lowest in the Nifty Realty index. GARCH in Mean analysis indicates that out of 11 sectoral indices, the Nifty Metal index and the Nifty PSU Bank index exhibit a significant GARCH value, indicating that the average mean returns of the metal industry and PSU Bank sector depend on their variance or risk. The results indicate that the risks in these markets lead to higher volatility, and taking on these risks yields higher returns. This increased risk or volatility allows investors to earn high returns by taking higher risks when investing in these sectors. Other indices exhibit an insignificant GARCH value, indicating that risk in these sectors does not yield higher returns from investments, as mean returns are not dependent on risk in those industries. This result is consistent with the results of Khera et al. (2022), which also reveal a risk-rewarding possibility in the Nifty Metal sectoral index.

Table 4: GARCH (1, 1) Output

Index	λ_0	λ_1	λ_2	$\lambda_1 + \lambda_2$
Nifty Auto	0.000006 (0.0000)	0.100941 (0.0000)	0.868325 (0.0000)	0.96927
Nifty Bank	0.000004 (0.0000)	0.090421 (0.0000)	0.889829 (0.0000)	0.98806
Nifty Financial Services	0.000005 (0.0000)	0.092959 (0.0000)	0.878995 (0.0000)	0.97195
Nifty FMCG	0.000004 (0.0000)	0.065782 (0.0000)	0.888979 (0.0000)	0.95476
Nifty IT	0.000006 (0.0000)	0.056117 (0.0000)	0.906218 (0.0000)	0.96234
Nifty Media	0.000023 (0.0000)	0.085767 (0.0000)	0.839074 (0.0000)	0.92484
Nifty Metal	0.000013 (0.0000)	0.059702 (0.0000)	0.896705 (0.0000)	0.95641
Nifty pharma	0.000006 (0.0000)	0.067625 (0.0000)	0.892774 (0.0000)	0.96040
Nifty PSU Bank	0.000060 (0.0000)	0.155245 (0.0000)	0.717818 (0.0000)	0.87306
Nifty Private Bank	0.000004 (0.0000)	0.087479 (0.0000)	0.892558 (0.0000)	0.98004
Nifty Realty	0.000049 (0.0000)	0.120336 (0.0000)	0.751438 (0.0000)	0.87177

Source: Computed Data.

Table 5: GARCH-in- Mean Output

Index	λ_0	λ_1	λ_2	$\lambda_1 + \lambda_2$	β
Nifty Auto	0.00001 (0.0000)	0.10183 (0.0000)	0.86662 (0.0000)	0.96845	0.11612 (0.1609)
Nifty Bank	0.00000 (0.0000)	0.09140 (0.0000)	0.88829 (0.0000)	0.97969	0.12865 (0.0763)
Nifty Financial Services	0.00000 (0.0000)	0.09377 (0.0000)	0.87776 (0.0000)	0.97152	0.14243 (0.0645)
Nifty FMCG	0.00000 (0.0000)	0.06593 (0.0000)	0.88882 (0.0000)	0.95474	-0.07290 (0.5050)
Nifty IT	0.00001 (0.0000)	0.05580 (0.0000)	0.90674 (0.0000)	0.96254	0.03116 (0.7834)
Nifty Media	0.00003 (0.0000)	0.09036 (0.0000)	0.82540 (0.0000)	0.91576	0.21942 (0.0683)
Nifty Metal	0.00001 (0.0000)	0.06274 (0.0000)	0.88919 (0.0000)	0.95193	0.38160 (0.0013)
Nifty pharma	0.00001 (0.0000)	0.06803 (0.0000)	0.89152 (0.0000)	0.95955	0.12333 (0.2565)
Nifty PSU Bank	0.00006 (0.0000)	0.16193 (0.0000)	0.70876 (0.0000)	0.87069	0.25427 (0.0301)
Nifty Private Bank	0.00000 (0.0000)	0.08816 (0.0000)	0.89149 (0.0000)	0.97965	0.12877 (0.0771)
Nifty Realty	0.00005 (0.0000)	0.12125 (0.0000)	0.74754 (0.0000)	0.86879	0.14233 (0.2397)

Source: Computed Data.

4.5. Investigating the presence of volatility asymmetry in returns of sectoral Indices

The EGARCH model is employed to examine the presence of volatility asymmetry, also known as the leverage effect, in the return series of all sectoral indices. If the value of the GARCH coefficient (λ_2) $It\ It$ It is close to unity, which indicates that volatility is persistent in the market. If the asymmetric coefficient (δ) Yields a significant negative value, which suggests that volatility asymmetry is present in the market. Table 5 presents the results of the EGARCH analysis.

Results show that the ARCH and GARCH coefficients (λ_1 and λ_2) For all sectoral indices, give positive and significant values, indicating that the present-day variance or shock has an impact on the prediction of future variances in returns, and these terms can explain volatility persistence in the sectoral indices. The ARCH (λ_1) The coefficient indicating the magnitude effect gives a significant positive value for all indices, confirming that volatility strongly reacts to market shocks and present-day volatility significantly affects the future returns of all sectoral indices. The GARCH (λ_2) Coefficient, indicating volatility persistence, shows a positive and significant value close to unity for all sectoral indices. This indicates that volatility is persistent in all these markets. The high coefficient value suggests that volatility will decay slowly.

In the EGARCH model, the asymmetric coefficient (δ) Values for all sectoral indices exhibit a significant negative value, confirming that volatility asymmetry or the leverage effect is present in these markets. This means that investors in these markets are more likely to be influenced by negative news than by positive news. The asymmetric coefficient (δ) Is less than zero for all indices, revealing that in these markets, negative news or shocks have a significant effect on volatility than positive shocks or news. This result is consistent with the findings of Sudhakar &Viswanadh (2018) and Mallikarjuna & Rao (2017), which also confirm that in sectoral indices, negative news creates high volatility, indicating that negative news has a higher impact on volatility than positive news.

Table 6: EGARCH Output

Index	λ_0	λ_1	λ_2	δ
Nifty Auto	-0.40861 (0.0000)	0.14292 (0.0000)	0.96590 (0.0000)	-0.07370 (0.0000)
Nifty Bank	-0.26457 (0.0000)	0.13808 (0.0000)	0.98173 (0.0000)	-0.06956 (0.0000)
Nifty Financial Services	-0.28128 (0.0000)	0.13467 (0.0000)	0.97978 (0.0000)	-0.07640 (0.0000)
Nifty FMCG	-0.36487 (0.0002)	0.10672 (0.0000)	0.96918 (0.0000)	-0.03037 (0.0176)
Nifty IT	-0.34447 (0.0000)	0.11737 (0.0000)	0.97052 (0.0000)	-0.03629 (0.0029)
Nifty Media	-0.38775 (0.0000)	0.12828 (0.0000)	0.96456 (0.0000)	-0.05876 (0.0000)
Nifty Metal	-0.40196 (0.0000)	0.11073 (0.0000)	0.96098 (0.0000)	-0.06269 (0.0000)
Nifty pharma	-0.56441 (0.0000)	0.15918 (0.0000)	0.95019 (0.0000)	-0.05754 (0.0000)
Nifty PSU Bank	-0.55002 (0.0001)	0.13760 (0.0000)	0.94274 (0.0000)	-0.02890 (0.0281)
Nifty Private Bank	-0.26457 (0.0000)	0.13785 (0.0000)	0.98171 (0.0000)	-0.06763 (0.0000)
Nifty Realty	-0.81913 (0.0000)	0.19353 (0.0000)	0.91491 (0.0000)	-0.07213 (0.0000)

Source: Computed Data.

5. Conclusion

Investors in the stock market always expect returns from their investments. Their trading is based on fundamental and technical analysis, and portfolio diversification helps them manage their trading more effectively. However, volatility in the stock market creates huge risks for investors. Identifying and analysing volatility in security prices is essential for reducing risks and earning returns.
The objective of this study was to identify and analyse volatility persistence present in 11 major sectoral indices of the NSE: Nifty Auto, Nifty Bank, Nifty Financial Services, Nifty FMCG, Nifty IT, Nifty Media, Nifty Metal, Nifty Pharma, Nifty Private Bank, Nifty PSU Bank, and Nifty Realty. Two symmetrical models, viz. GARCH (1,1) and GARCH-in-Mean models were used to analyse volatility. Both models gave positive and significant ARCH and GARCH coefficients (λ_1 and λ_2) For all indices, indicating that past residuals and past conditional variances of returns can explain and predict volatility persistence. Volatility persistence is highest in the Nifty Bank index and lowest in the Nifty Realty index, as observed in both GARCH models. For all sectoral indices, in both models, the sum of $\lambda_1 + \lambda_2$ The coefficient values are close to 1, indicating that a high degree of volatility is persistent in all these sectors.
Out of 11 sectoral indices, only the Nifty Metal index and Nifty PSU Bank index show a significant GARCH coefficient, indicating that increased volatility has the potential to generate high returns. So, investors can earn high returns from the risk taken on investment in these sectors. In the case of other indices, risk-taking does not generate high returns. The EGARCH results for all sectoral indices indicate a significant negative effect, suggesting that the leverage effect is present in all these markets, confirming that negative news has a greater impact than positive news. The findings of this study help investors identify sectors that offer risk premiums or high returns, which is essential for their investment decisions. This study throws light on the volatility persistence of sectoral indices returns. It educates investors about the importance of analysing and modelling the volatility of returns before investing in the stock market.

6. Policy Implications and Further Scope

This study contributes to the existing finance literature by analysing the volatility persistence, risk-return relationship, and leverage effect in major sectoral indices of the NSE. This study helps investors identify the sectors and stocks that will earn profit for a particular risk they bear. This allows them to create a healthy portfolio or efficiently diversify existing portfolios by focusing on profitable sectors, such as metals. Academicians and students can utilise this study to gain an understanding of volatility, persistence, and the leverage effect in the major Nifty Sectoral Indices, as well as how these factors impact the market. Financial brokers and consultants can utilise the findings of this study to enhance their advisory services by evaluating market situations, volatility, and the leverage effect, and inform investors regarding investment decisions through alternative options. Industries or companies included in each sectoral index can use this study to evaluate the presence of volatility and the leverage effect in stock prices, which deters investors from investing in their stocks.
Researchers can extend the methodology of this study to other indices in the NSE, such as Strategy Indices, Thematic Indices, and Government Securities Indices. This study used only models, viz. GARCH (1,1), GARCH-in-Mean, and EGARCH models. Researchers can use other models from the GARCH family to capture and analyse the presence of volatility and its impact on sectoral indices.

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Author Declarations

Availability of Data and Material

The datasets used and/or analysed during the current study are available from the corresponding author on reasonable request.

Competing Interests

The authors declare that they have no competing interests.

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Authors' Contribution

LA collected and constructed the data, conducted the quantitative analysis, and wrote the whole paper. VGK supervised and edited the paper. All authors read and approved the final manuscript.

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