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The Impact of Market Sentiment on Sectoral Returns: A Behavioral Analysis Using India VIX and NIFTY Sectoral Data

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ABSTRACT

This study examines the influence of market sentiment, measured through the India Volatility Index (India VIX), on sectoral returns in the Indian equity market between 2014 and 2024. Using daily data from the National Stock Exchange to analyse the linkages between sentiment and sectoral returns, the study utilizes correlation measures, regression, volatility estimation through GARCH models, and Granger causality approaches

The results indicate that sentiment reveals a significant but different impact across sectors. Financial services and banking are the most vulnerable, showing significant declines during spikes in India VIX, while defensive sectors such as FMCG, healthcare, and IT display relative stability, serving as safer investment avenues during periods of uncertainty. Distributional analysis highlights non-normal features such as fat tails, skewness, and persistent volatility clustering, reinforcing the behavioral complexity of market movements.

Causality findings reveal that market fear not only drives returns in several sectors but is also influenced by sectoral performance in industries like automobiles, suggesting that investor psychology and sectoral dynamics reinforce each other in cyclical patterns. Overall, the study brings in the importance of incorporating investor sentiment into financial analysis and strategy. The results hold practical relevance for portfolio managers, policymakers, and researchers seeking to understand and mitigate sentiment-driven risks in emerging markets.

Keywords: India VIX, Sectoral Returns, Market Sentiment, Volatility, Behavioral Finance, Investor Sentiment, Equity Markets, Emerging Economies

Introduction

Collective behavior and emotions of people drive the financial markets along with numbers, this is proven in times of uncertainty. The traditional finance theories, mainly the Efficient Market Hypothesis (EMH), argue that prices fully and rationally adjust in such a way that they incorporate all information accessible to investors, leaving less focus for the sentiment or psychology of the people. When there are shifts in sentiment during market anomalies, bubbles, and crashes, the traditional finance theory contradicts the real-world scenario, as it unexpectedly affects the economic system. (Barberis & Thaler, 2003; Fama, 1970)

The Behavioral finance, which emphasizes the role of cognitive biases and sentiment in shaping market outcomes, has argued that people's emotions, such as fear, optimism, greed, and herding tendencies, often influence investment decisions by contradicting financial fundamentals. Indian markets are fast evolving in the world; the investor sentiment impacts the returns in the market, which brings light to a deeper understanding of behavioral undercurrents.(Baker & Wurgler, 2007; Kahneman & Tversky, 1979)

Volatility Index(VIX), known as 'fear gauge', is the widely accepted measure of sentiment that captures market expectation of future volatility, which is based on option prices. The higher VIX signals the increased uncertainty and nervousness of investors in the market. The India VIX, modelled based on the Chicago Board Options Exchange (CBOE) VIX, has a crucial role in the Indian Equity market, which offers a Quantitative measure of market fear and anticipated volatility. Even with significant research attention on all market-wide indices, namely NIFTY 50 or Sensex, there are sectoral differences.(Sarwar, 2012; Whaley, 2000)

Every industry is different in reacting to the sentiments; for example, Financial services and Banking are more exposed to investor fear due to factors like liquidity, credit cycles, and uncertain macroeconomic changes. Whereas sectors like health care, IT, FMCG, and pharmaceuticals remain resilient during market fluctuations, in between are moderately sensitive sectors such as consumer durables, auto, or oil and gas, which mirror investor sentiment shifts but retain moderate strength (Chandra & Kumar, 2011; Barberis et al., 1998). By analyzing the India VIX and sectoral returns from 2014–2024, this study contributes to the literature on sentiment and sectoral performance, offering empirical evidence of their interrelationship in the Indian context. This study draws on tools like OLS regression, GARCH models, and Granger causality tests to explore how shifts in market sentiment spill over into different sectors of the Indian equity market. The results reveal clear sectoral differences in how markets react to fear, while also shedding light on the persistence of volatility and the mutual influences that connect sentiment with sectoral returns.

Literature review

Investor sentiment is widely recognized as a powerful driver of stock market dynamics, shaping not only aggregate returns but also the performance of individual sectors. Its influence becomes especially considerable during periods of heightened uncertainty, a theme that has been examined in depth across both theoretical frameworks and empirical investigations. Classic study by Fama (1970) The Efficient Market Hypothesis (EMH) provides a foundational benchmark, suggesting that markets incorporate all available information. However, evidence from behavioral finance challenges this notion, highlighting systematic deviations from fundamentals caused by cognitive biases and investor psychology (Barberis et al., 1998; De Bondt & Thaler, 1985)

The Volatility Index (VIX) has emerged as a widely accepted proxy for market sentiment and risk perception. Whaley (2000, 2009)demonstrated the VIX's ability to reflect expected 30-day volatility derived from option prices, confirming its role as the "investor fear gauge." Notably, VIX exhibits a nonlinear association with returns: market declines provoke sharper increases in VIX than the declines observed during rising markets, emphasizing its relevance in capturing investor anxiety. Subsequent studies by Bekaert & Hoerova (2014) further decompose VIX into conditional variance and variance risk premium, illustrating that different components of volatility can offer complementary insights into risk and return dynamics.

Empirical studies focusing on the Indian context provide strong evidence of the VIX's relevance for emerging markets. Smales (2017) shows that VIX-based fear measures lead

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short-term market returns, with small-cap, growth, and technology stocks particularly sensitive to sentiment fluctuations. Aggarwal (2017)confirms that in India, shifts in investor mood captured through the Market Mood Index (MMI) and VIX exert significant influence on contemporaneous returns, with Granger causality indicating predictive power in certain sectors. Similarly, Chakrabarti & Kumar (2020) identify a negative and nonlinear association between Nifty returns and India VIX, emphasizing the behavioral underpinnings of volatility spikes during market declines.

Sectoral analyses highlight that sentiment does not affect all industries uniformly. Law (2024) examines sectoral stock price dynamics across multiple countries, including India, and finds that sectoral returns exhibit varying volatility, interdependencies, and sensitivity to macroeconomic and sentiment-driven shocks. Rohilla et al. (2023) and Kamath et al. (2024) further demonstrate that investor sentiment significantly impacts Indian sectoral indices, with the Automobile, Finance, Metal, and PSU sectors showing the strongest responsiveness. These findings underscore the importance of incorporating sentiment analysis when evaluating sector-specific market performance.

Recent advances integrate sophisticated econometric and machine learning techniques with sentiment data to predict market behavior more accurately. Ali et al. (2022) document persistent, clustered, and asymmetric volatility in Indian stock returns using GARCH family models, confirming that negative shocks amplify market risk more than positive shocks. Maddodi & Kunte (2024) combine linking online investor sentiment with conventional market measures (VIX, MACD, RSI) and LSTM neural networks to achieve high prediction accuracy for investment behavior under geopolitical uncertainty. Similarly, Chari et al. (2023) and Varghese & Mohan (2023)demonstrate the causal effect of financial news sentiment on asset price movements, with effects that are often short-lived but critical for short-term trading strategies.

Policy and macroeconomic interventions also interact with market sentiment. Bhattacharjee & De (2023) show that during the COVID-19 pandemic, government policy measures reduced market fear in high-fear regimes, as reflected in India VIX dynamics, highlighting the regime-dependent nature of investor sentiment. Forecasting efforts, such as those by Banerjee (2019),

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provide reliable near-term predictions of VIX, enhancing market timing and risk management strategies. Aggarwal (2017) emphasizes the importance of crisis-specific volatility drivers, including COVID-19 and geopolitical tensions, in shaping market behavior, reinforcing the relevance of behavioral analysis for both investors and policymakers.

Globally, studies such as Kirci Altinkeski et al. (2024) reveal nonlinear, time-varying relationships between VIX and returns, with spillovers stronger in developed markets but observable in emerging economies as well. Behavioral studies by Brown & Cliff (2004), Ding et al. (2021), and Lee et al. (2002) consistently show that investor sentiment acts as a priced risk factor, influencing both returns and volatility across multiple market contexts.

In summary, prior studies show that market sentiment, measured through proxies like the VIX, investor mood indices, and news-based indicators, has a significant, and often asymmetric, impact on overall market performance as well as sector-specific returns. Empirical evidence from India shows that the impact of sentiment is not uniform across sectors; it is heterogeneous, changes over time, and becomes stronger during periods of financial stress or crisis. Together, these studies offer a solid theoretical and empirical base for examining how market sentiment shapes NIFTY sectoral indices through the lens of the India VIX, aligning well with the objectives and methods of the present study.

Research methodology

1. Objectives of the study
    1. To examine how market sentiment, captured by the India VIX, influences the returns of different NIFTY sectoral indices.
    2. To classify NIFTY sectors according to their sensitivity to market volatility, using correlation analysis with the India VIX.
    3. To examine the relationship between India VIX and sectoral returns through regression analysis and volatility modeling techniques.
    4. To examine the causal linkages between the India VIX and sectoral returns, with a focus on how shifts in market sentiment and sectoral performance influence each other over time.

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Data Selection and Sources

- **Dataset Composition:**
  Daily closing prices of sectoral indices (Media, Pharma, Private Bank, PSU Bank, Oil & Gas, Healthcare, Financial Services, IT, Metal, etc.) and the India VIX were obtained for analysis.
- Time Period:
  The study examines data from January 1, 2014, to December 31, 2024, capturing major market cycles and periods of both low and high volatility.
- **Data Sources:**
  All financial data were sourced from the National Stock Exchange of India to ensure accuracy and consistency.

2. **Data Preparation**
   - Return Calculation:
     Logarithmic daily returns were calculated for all sectoral indices and India VIX to address non-normality and provide standardization for time-series modelling
3. **Descriptive and Distributional Analysis**
   - Statistical Summary:
     For each sectoral return series, the mean, median, standard deviation, skewness, kurtosis, minimum, maximum, and Jarque-Bera test statistics were computed to evaluate distributional characteristics, including fat tails, asymmetry, and deviations from normality.
   - Panel Stationarity Testing:
     Panel unit root tests (Levin, Lin & Chu, Im, Pesaran & Shin, ADF-Fisher, PP-Fisher) confirmed all series were stationary at the level, validating their use for regression and GARCH modeling.
4. **Econometric Modeling**
   - OLS Regression:
     Ordinary Least Squares regression was performed for each sectoral log return against the log difference of India VIX. Results reported include coefficients, t-statistics, p-

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values, R^2, and Durbin-Watson statistics, quantifying sectoral sensitivity to changes in market sentiment.

- GARCH Volatility Modeling:

  Each sector's volatility was modeled using univariate GARCH(1,1) processes. The model included India VIX in the mean equation, with focus on the magnitude and significance of VIX coefficients, ARCH (α_1), GARCH (β_1), and overall volatility persistence ($\alpha + \beta$).

5. **Dynamic Linkage and Causality Tests**

- Granger Causality:

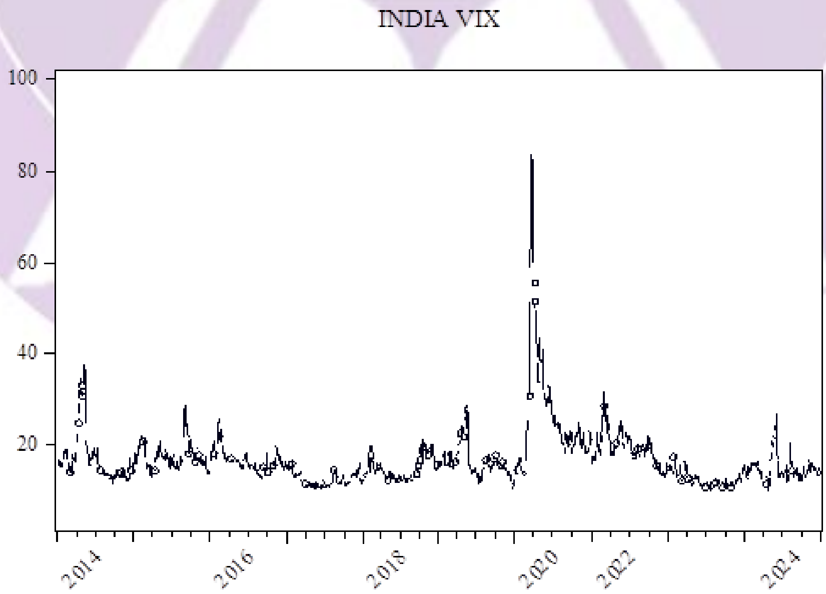
  Granger causality tests probed for bidirectional and unidirectional influences between India VIX and each selected sector's returns, using optimal lags determined by information criteria. Directionality was tabulated for a robust understanding of market sentiment transmission

- Reporting of Causality:

  Each sector's p-value and causal direction (India VIX→Sector, Sector→India VIX, or bi-directional) were documented to highlight dynamic relationships.

Data analysis

Figure I: Representation of India VIX daily values



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The line chart in figure I presents the daily value of the INDIA VIX from 2014 through 2024, showing changes in overall market volatility expectations within the Indian equity market. The major spike can be seen in 2020, with the VIX value reaching 80. The event that contributed to this spike was the COVID-19 pandemic, which resulted in panic among the investors. The sharp and sudden jump in volatility was far greater than anything seen before or after, making it clear that the pandemic was not just another market event but a rare shock that changed how investors viewed risk and led many to rethink and adjust their portfolios.

Following the initial pandemic shock, the VIX declined sharply, reverting to more normal, though still elevated, levels. Post-2020, the India VIX exhibits moderate fluctuations with occasional spikes, suggesting that although investor anxiety eased as markets adjusted to pandemic conditions, occasional periods of high uncertainty remained. This pattern matches what is known as volatility clustering, where quiet stretches in the market are broken by sudden risk and then slowly return to normal.

Descriptive Statistics

Table I: Panel A: Mean, Median, Standard Deviation, Minimum, Maximum

Index	Mean	Median	Std. Dev.	Min	Max
Media	-0.0001	0.0006	0.0804	-0.1788	0.0168
Pharma	0.0004	0.0005	0.0987	-0.0935	0.0124
Private Bank	0.0006	0.0007	0.1049	-0.1969	0.0143
PSU Bank	0.0002	0.0000	0.2595	-0.1641	0.0210
Oil and Gas	0.0005	0.0008	0.0868	-0.1255	0.0138
Nifty500 Healthcare	0.0006	0.0012	0.0831	-0.0853	0.0107
MidSmall Financial Services	0.0005	0.0015	0.0679	-0.1889	0.0145
MidSmall Healthcare	0.0009	0.0013	0.0624	-0.1054	0.0106

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MidSmall IT & Telecom	0.0006	0.0014	0.0636	-0.1352	0.0131
METAL	0.0003	0.0008	0.0939	-0.1233	0.0176
IT	0.0004	0.0005	0.0864	-0.1006	0.0129
Nifty Auto	0.0005	0.0010	0.0990	-0.1491	0.0135
Bank	0.0006	0.0008	0.1000	-0.1831	0.0141
Chemicals	0.0007	0.0013	0.0554	-0.1457	0.0122
Consumer Durables	0.0008	0.0011	0.0741	-0.1204	0.0119
Financial Services	0.0006	0.0013	0.0810	-0.1958	0.0142
Financial Services 25/50	0.0006	0.0009	0.0891	-0.1736	0.0135
Fin. Services Ex-Bank	0.0006	0.0010	0.0903	-0.1830	0.0135
FMCG	0.0004	0.0006	0.0799	-0.1120	0.0105
Healthcare	0.0005	0.0007	0.0880	-0.0869	0.0115

Most sectors showed small but positive average (mean) and median daily returns in the table I, indicating general stability, though Media showed a slight negative mean return (–0.0001), showing mild underperformance. Volatility varies widely across sectors. PSU Bank stands out with the highest standard deviation (0.2595), meaning it’s the most unpredictable and carries the most risk. In contrast, MidSmall Healthcare (0.0624) is among the least volatile, offering more stable returns. Private Bank experienced the largest daily loss (–0.1969), which underscores high risk; meanwhile, sectors like Oil and Gas and MidSmall Healthcare saw much smaller worst-case declines (–0.1255, –0.1054). Maximum daily gains across all sectors are modest, typically below 2%, showing that sharp losses tend to outsize sudden rallies. Volatility and risk are far from uniform. PSU and Private Banks are much more volatile than, say, IT or MidSmall Healthcare.

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Table II: Panel B: Skewness, Kurtosis, Jarque-Bera Statistic, Probability

Index	Skewness	Kurtosis	JB Stat.	Probability
Media	-1.0753	12.6523	10072.62	0.0000
Pharma	-0.1689	8.3439	2953.11	0.0000
Private Bank	-1.2895	24.1774	46878.54	0.0000
PSU Bank	0.4305	16.3681	18483.06	0.0000
Oil and Gas	-1.0578	15.0068	15309.90	0.0000
Nifty500 Healthcare	-0.5190	10.0480	5227.44	0.0000
MidSmall Financial Services	-1.7256	18.7078	26640.65	0.0000
MidSmall Healthcare	-1.1153	12.9450	10699.56	0.0000
MidSmall IT & Telecom	-1.0388	11.7025	8245.06	0.0000
METAL	-0.5317	6.9597	1731.48	0.0000
IT	-0.4138	9.1635	3983.34	0.0000
Nifty Auto	-0.6408	14.4077	13573.09	0.0000
Bank	-1.1512	20.7111	32855.48	0.0000
Chemicals	-1.2071	14.4559	14117.81	0.0000
Consumer Durables	-0.6301	11.2674	7203.69	0.0000
Financial Services	-1.6837	22.5976	40726.55	0.0000
Financial Services 25/50	-1.2502	20.4129	31874.50	0.0000

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Fin. Services Ex-Bank	-1.4620	22.4533	39858.89	0.0000
FMCG	-0.4456	14.3271	13297.05	0.0000
Healthcare	-0.2888	8.4066	3045.17	0.0000

Most sectors in Table II exhibited negative skewness (e.g., Mid-Small Financial Services at –1.73, Private Bank at –1.29), showing that sharp losses tend to occur more often than sharp gains. Only PSU Bank shows a positive skew (0.43), indicating that it experienced more frequent positive price jumps. All sectors exhibit kurtosis much higher than 3 (the benchmark for a normal distribution), indicating “fat tails”, in other words, large price moves, both up and down, happen more often than would be expected. Private Bank, for example, has a very high kurtosis of 24.18. These measures make it clear that sudden sharp drops are not accidents but a regular feature of sector returns. Defensive sectors such as FMCG, Healthcare, and IT tend to provide relatively stable and reliable returns, whereas financials and banking demand greater caution, particularly during volatile periods. With very high JB statistics and all p-values at 0.0000, the evidence strongly shows that these return distributions cannot be considered normal. Such behavior is characteristic of financial returns, reinforcing the need for methodologies that explicitly model extreme risks and persistent volatility.

ADF Stationarity Tests

All panel unit root tests (Levin, Lin & Chu; Im, Pesaran and Shin; ADF-Fisher; PP-Fisher) reject the null hypothesis of non-stationarity at a 1% significance level. The log return series of the sectoral indices and the India VIX are found to be stationary, which justifies their use in regression and GARCH frameworks. Stationarity is important because it ensures that any detected relationships reflect true market behavior rather than spurious correlations.

Correlations and Covariances with India VIX

Strong negative correlations and small negative covariances indicate that sectors move inversely with market volatility spikes. Financial and banking sectors have the highest negative correlations (around -0.47 to -0.51), indicating that they are most exposed to market fear.

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Defensive sectors like IT and Healthcare show lower sensitivity, indicating that investors tend to favor these sectors during volatile periods

Sector Classification Based on Correlation with India VIX

Sectors are grouped by sensitivity to market sentiment reflected in the India VIX:

- Highly Sensitive sectors show strong negative correlation (≤ -0.47), indicating sharp declines during high volatility periods (e.g., MidSmall Financial Services: -0.512).
- Moderately Sensitive sectors have moderate negative correlations (-0.47 to -0.40), suggesting some resilience mixed with risk perception (e.g., Media: -0.431, Oil Natural Gas: -0.428).
- Defensive sectors have weak negative or near-zero correlation (≥ -0.40), considered safe havens (e.g., FMCG: -0.358, IT: -0.306).

Table III: Highly Sensitive Sectors

Sector	Corr. with VIX	Cov. with VIX
Midsmall Financial Services	-0.512	-0.000386
Financial Services Ex Bank	-0.505	-0.000374
Financial Services 25/50	-0.503	-0.000356
Financial Services	-0.479	-0.000338
Bank	-0.473	-0.000347
Chemicals	-0.471	-0.000299
Private Bank	-0.470	-0.000349
Auto	-0.470	-0.000332
Metal	-0.463	-0.000425

Table III shows that the Sectors in the highly sensitive sectors category show the strongest negative correlation with India VIX (≤ -0.47), indicating that they are highly exposed to market volatility. MidSmall Financial Services (-0.512) records the highest sensitivity, followed by Financial Services ex Bank (-0.505), and Financial Services 25/50 (-0.503). The broader banking segment, including Private Banks (-0.470) and Banks (-0.473), tends to be more

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sensitive. Auto (-0.470), Metals (-0.463), and Chemicals (-0.471) Such evidence reinforces the cyclical tendencies of these industries, as volatility and sentiment swings trigger sharp return declines. The cluster shows that financial and cyclical sectors are most vulnerable during phases of elevated market uncertainty

Table IV: Moderately Sensitive sectors

Sector	Corr. with VIX	Cov. with VIX
Media	-0.431	-0.000378
Midsmall IT Telecom	-0.432	-0.000295
Oil Natural Gas	-0.428	-0.000307
Consumer Durables	-0.411	-0.000256
Midsmall Healthcare	-0.402	-0.000222

Table IV shows that with correlations ranging from –0.47 to –0.40, moderately sensitive sectors display a clear but less intense reaction to risk. Media (-0.431), Oil & Natural Gas (-0.428), and Consumer Durables (-0.411) show the influence of Cyclical consumption demand and global commodity cycles, which tend to fluctuate under uncertain market conditions. MidSmall IT & Telecom (-0.432) and MidSmall Healthcare (-0.402) also come in this range, suggesting that while smaller firms are somewhat exposed, they are less affected compared to financials or cyclical industries. Taken together, these sectors show a balanced ability to withstand volatility, which affects them only to a limited extent.

Table V: Defensive sectors

Sector	Corr. with VIX	Cov. with VIX
PSU Bank	-0.396	-0.000434
Nifty500 Healthcare	-0.389	-0.000216
Pharma	-0.328	-0.000212
Healthcare	-0.349	-0.000209
FMCG	-0.358	-0.000196
IT	-0.306	-0.000206

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Defensive sectors in Table V show weaker correlations with the India VIX (≥ –0.40), highlighting their relative stability during volatile market phases. Among them, FMCG (–0.358) and IT (–0.306) stand out as the least sensitive, owing to their demand-driven nature, which helps them remain resilient even when broader markets fluctuate. Healthcare (–0.349), Nifty500 Healthcare (–0.389), and Pharma (–0.328) also show resilience, supported by the relatively inelastic demand for healthcare, which makes these sectors less tied to the economic cycle. PSU Banks (–0.396) appear less exposed than private banks, helped by government support. This implicit safety net makes them a stabilizing force and offers investors a relatively safer haven during periods of market stress.

The classification reveals clear patterns in how sectors respond to market volatility. Financial and cyclical sectors prove to be the most sensitive, given their strong reliance on shifts in investor sentiment and broader economic conditions. Sectors in the middle range show moderate responses, balancing market exposure with some resilience. In contrast, defensive sectors stay largely insulated and act as a stabilizing buffer during periods of high volatility. Overall, these patterns suggest that portfolio strategies need to account for sector-specific sensitivity when making allocation choices.

Table VI: OLS Regression Results

Sector	Constant (C)	Coef. (VIX Log Diff)	t-Stat	p-Value	R^2	Adj. R^2	D-W Stat
MidSmall Financial Services	0.0005	-0.1417	-29.62	0.0000	0.262	0.262	1.80
Financial Services Ex Bank	0.0006	-0.1371	-29.12	0.0000	0.256	0.255	1.89
Financial Services 25/50	0.0006	-0.1304	-28.92	0.0000	0.253	0.253	1.91
Financial Services	0.0006	-0.1238	-27.15	0.0000	0.230	0.229	1.93
Bank	0.0005	-0.1274	-26.66	0.0000	0.223	0.223	1.89
Chemicals	0.0007	-0.1097	-26.57	0.0000	0.222	0.222	1.87
Private Bank	0.0006	-0.1281	-26.43	0.0000	0.220	0.220	1.88

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Auto	0.0005	-0.1217	-26.47	0.0000	0.221	0.221	1.90
Metal	0.0003	-0.1558	-25.99	0.0000	0.215	0.214	1.98
Media	-0.0001	-0.1384	-23.74	0.0000	0.186	0.185	2.03
Midsmall IT& Telecom	0.0006	-0.1080	-23.82	0.0000	0.187	0.186	1.79
Oil & Natural Gas	0.0005	-0.1126	-23.50	0.0000	0.183	0.182	1.98
Consumer Durables	0.0008	-0.0939	-22.39	0.0000	0.169	0.168	1.85
Midsmall Healthcare	0.0009	-0.0815	-21.84	0.0000	0.162	0.161	1.81
Psu Bank	0.0002	-0.1592	-21.47	0.0000	0.157	0.157	1.94
Nifty 500 Healthcare	0.0006	-0.0793	-20.96	0.0000	0.151	0.151	1.86
Pharma	0.0004	-0.0776	-17.27	0.0000	0.108	0.107	1.93
Healthcare	0.0005	-0.0767	-18.51	0.0000	0.122	0.121	1.90
FMCG	0.0004	-0.0720	-19.08	0.0000	0.128	0.128	2.05
IT	0.0004	-0.0755	-15.97	0.0000	0.094	0.093	2.04

The OLS Regression results in Table VI show that the Coefficients for India VIX log differences are negative and statistically significant (p-value = 0.000 across sectors), demonstrating that increases in market volatility negatively impact sectoral returns. The magnitude of regression coefficients varies in line with sectoral sensitivity. For instance, MidSmall Financial Services (–0.1417) demonstrates stronger reactivity to market volatility compared to the IT sector (–0.0755). The explanatory power, as indicated by R-squared values, also varies across sectors: financial sectors generally exhibit higher explanatory strength (~0.25), whereas sectors such as IT show comparatively weaker explanatory capacity (~0.09). Durbin–Watson statistics remain close to 2 across all models, suggesting the absence of significant autocorrelation in residuals. Collectively, these findings highlight that market sentiment plays a decisive role in shaping sectoral returns, thereby lending empirical support to the theoretical propositions of behavioral finance.

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Table VII: GARCH Model Results

Sector	Coef. (VIX)	z-Stat	p-Value	ARCH (α1)	GARCH (β1)	α + β
Bank	-0.1249	-33.21	0.0000	0.0901	0.8810	0.9711
Auto	-0.1092	-35.26	0.0000	0.0942	0.8598	0.9540
Chemicals	-0.1025	-34.78	0.0000	0.0850	0.8756	0.9606
Consumer Durables	-0.0874	-29.65	0.0000	0.0918	0.8804	0.9722
Fin Services Ex Bank	-0.1338	-38.12	0.0000	0.0964	0.8895	0.9859
Financial Services	-0.1206	-36.44	0.0000	0.0895	0.8822	0.9717
Financial Services 25/50	-0.1293	-37.96	0.0000	0.0946	0.8870	0.9816
FMCG	-0.0662	-25.10	0.0000	0.0777	0.8722	0.9499
Healthcare	-0.0711	-22.74	0.0000	0.0804	0.8648	0.9452
IT	-0.0703	-21.23	0.0000	0.0893	0.8813	0.9706
Media	-0.1335	-30.84	0.0000	0.0925	0.8770	0.9695
Midsmall Fin Services	-0.1397	-39.21	0.0000	0.0996	0.8924	0.9920
Midsmall Healthcare	-0.0764	-24.12	0.0000	0.0873	0.8612	0.9485
Midsmall It Telecom	-0.0993	-27.35	0.0000	0.0949	0.8673	0.9622
Nifty500 Healthcare	-0.0732	-23.76	0.0000	0.0820	0.8744	0.9564
Oil Natural gas	-0.1064	-27.89	0.0000	0.0915	0.8840	0.9755
Private Bank	-0.1239	-33.80	0.0000	0.0881	0.8762	0.9643
Psu Bank	-0.1533	-29.47	0.0000	0.0956	0.8828	0.9784
Pharma	-0.0776	-17.27	0.0000	0.0860	0.8694	0.9554
Metal	-0.1558	-25.99	0.0000	0.0972	0.8846	0.9818

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1. Mean Equation Results (Effect of India VIX on Returns)

Across all sectors, shown in Table VII, the estimated coefficients for India VIX are negative and statistically significant, showing that an increase in market volatility reduces sectoral returns. The size of the coefficient varies by sector, highlighting different levels of sensitivity.

- Most affected sectors include Metal (-0.1558), PSU Banks (-0.1533), and MidSmall Financial Services (-0.1397). These sectors tend to react more sharply to changes in investor sentiment and market uncertainty.
- Moderately impacted sectors such as Auto (-0.1092), Oil & Natural Gas (-0.1064), and Chemicals (-0.1025) show noticeable downfall during volatile periods, though less severe than financials and metals.
- Relatively stable sectors, including FMCG (-0.0662), IT (-0.0703), and Healthcare (-0.0711), show weaker responses, consistent with their reputation as defensive industries.

These findings indicate that although market volatility influences all sectors, the degree of impact differs depending on each sector's fundamentals and how investors perceive them

2. Variance Equation Results (Volatility Persistence)

The volatility parameters, captured through ARCH and GARCH components, illustrate how shocks to returns propagate over time. The ARCH term (α_1), representing the immediate effect of new shocks, ranges from 0.08 to 0.10 across sectors, indicating that sudden spikes in volatility have a short-term impact on returns. In contrast, the GARCH term (β_1), which lies between 0.86 and 0.89, is substantially larger, highlighting the strong and persistent influence of past volatility on current returns.

The sum of α and β values is close to one across all sectors, ranging from 0.9452 for Healthcare to 0.9920 for MidSmall Financial Services. This indicates that volatility, once it rises, tends to persist rather than dissipate quickly. The effect of persistence is strongest in financials and mid-small firms, whereas sectors like healthcare and FMCG show comparatively lower persistence.

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3. Sectoral Insights

- **High volatility exposure:** Metals, PSU Banks, and financial subsectors experience sharp declines and prolonged volatility, making them highly vulnerable during market stress.
- **Moderate exposure:** Sectors such as Auto, Oil & Natural Gas, and Chemicals react noticeably but not as intensely.
- **Defensive profile:** FMCG, IT, and Healthcare are less sensitive to VIX shocks and show comparatively lower persistence, offering some stability when volatility increases.

The GARCH model results highlight two key findings: first, market volatility (India VIX) has a consistently negative impact on sectoral returns; second, volatility shocks are not short-lived but remain persistent across all industries. The degree of impact varies; financials and metals emerge as the most exposed, while FMCG, IT, and healthcare play a stabilising role. For investors and portfolio managers, these results emphasize the value of sectoral diversification, with defensive sectors acting as a buffer during prolonged periods of uncertainty.

Table VIII: Granger Causality Test Results (Selected Sectors)

Sector	Lag	India VIX → Sector (p-value)	Sector → India VIX (p-value)	Direction
Metal	5	0.0884	0.0006	Bi-directional
IT	3	0.0224	0.3148	Unidirectional (VIX → IT)
Auto	3	0.0726	0.0405	Unidirectional (AUTO → VIX)
Bank	4	0.0193	0.0564	Unidirectional (VIX → BANK)
FMCG	2	0.0094	0.389	Unidirectional (VIX → FMCG)
Financial services 25/50	2	0.0133	0.0053	Bi-directional

The Granger causality results in Table VIII reveal the sector-specific dynamics between India VIX and sectoral returns. In several cases, volatility is found to drive sectoral performance, as seen in IT ($p = 0.0224$), Banks ($p = 0.0193$), and FMCG ($p = 0.0094$), where the influence runs

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unidirectionally from VIX to sector returns. This indicates that these sectors largely react to broader market sentiment rather than shaping volatility themselves. In contrast, the Auto sector shows the opposite pattern, where causality runs from sectoral returns to VIX ($p = 0.0405$), suggesting that movements in Auto returns may serve as early signals for changes in market-wide uncertainty. Bi-directional linkages appear in Metals ($p = 0.0884$; $p = 0.0006$) and Financial Services 25/50 ($p = 0.0133$; $p = 0.0053$), showing that volatility both shapes and is shaped by sectoral performance. Although the India VIX remains the main driver, sector-level dynamics, especially in financial and cyclical sectors, amplify and spread volatility across the market.

Discussions

Sectoral Return Patterns

Between 2014 and 2024, most NIFTY sectoral indices posted modest positive daily returns, with the Media sector being the exception, showing slightly negative performance. Volatility varied widely across sectors: PSU Banks experienced the greatest instability, reflecting their exposure to policy changes and broader economic shocks, while MidSmall Healthcare remained relatively stable. Several sectors showed negative skewness and high kurtosis, meaning losses were generally steeper than gains, and extreme price movements happened more often than a normal distribution would predict. These observations align with Agarwal (2024), who noted that in recent years, Indian equity markets have been shaped by crises such as COVID-19, underscoring the need for advanced econometric models to analyze market behavior effectively.

Stationarity of Data

The panel unit root tests indicated that sectoral returns and India VIX changes were stationary, confirming that the statistical relationships captured are meaningful rather than random. This reliability provides a solid basis for applying regression and volatility models, echoing earlier Indian studies that relied on ARIMA and GARCH frameworks to analyze market sentiment and volatility (Ali et al., 2022; Banerjee, 2019).

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Sensitivity to Market Fear

Correlation results showed that sensitivity to India VIX differs by sector. Financial services and banking sectors were the most responsive, with sharp declines during periods of elevated fear. Media and Consumer Durables were moderately affected, while defensive areas like FMCG, Healthcare, and IT were comparatively less exposed. This sectoral divide mirrors findings by Smales (2017) and Kamath et al. (2024), who observed that sentiment shocks weigh heavily on cyclical and financially leveraged industries, while defensive sectors act as safer options for investors during turbulent times.

Impact of Volatility on Returns

Regression analysis confirmed that higher market fear generally coincides with lower returns. Financial sectors were hit the hardest, while defensive sectors also fell but to a lesser degree. This outcome is consistent with global evidence showing that markets drop more steeply when fear rises than they gain when optimism improves (Whaley, 2000, 2009). Indian studies such as Aggarwal (2017) and Yadav & Chakraborty (2022) also reported that increases in investor fear significantly drag down short-term returns, particularly for risk-sensitive stocks and sectors.

Volatility Behavior

The GARCH models revealed that volatility shocks do not fade quickly but tend to persist, especially in financial services. This persistence reflects how market fear can sustain elevated risk levels for extended periods, rather than disappearing after the initial shock. Similar patterns of clustering have been documented in international research (Bekaert & Hoerova, 2014)and in the Indian context by Chakrabarti & Kumar (2020), who found volatility spikes lingered through crisis phases.

Sentiment and Sector Dynamics

The causality analysis showed that interactions between sentiment and returns are not uniform across industries. In Metals and Financial Services, a feedback loop exists where sector performance and market fear reinforce one another. For sectors such as IT, Banking, and FMCG, sentiment largely drives returns, supporting the idea of the India VIX as a "fear gauge" (Rohilla et al., 2023; Shaikh & Padhi, 2013). Interestingly, the Auto sector displayed the reverse pattern, where sector movements influenced overall market sentiment. Such cases support Varghese & Mohan (2023), who argued that sentiment is not always external but can also be shaped by industry-specific developments and news.

Taken together, the evidence shows that India VIX plays a decisive role in shaping sectoral returns, though the strength of its influence varies across industries. Financial and cyclical sectors remain the most vulnerable to sentiment-driven shocks, while defensive sectors provide relative stability. The persistence of volatility and the presence of feedback effects in certain sectors support the behavioral finance view that markets often diverge from efficiency when shaped by emotions and biases (Barberis et al., 1998; De Bondt & Thaler, 1985). Building on earlier contributions (Kamath et al., 2022; Rohilla et al., 2023), this study demonstrates that sentiment shocks not only depress returns but can also amplify volatility through feedback loops at the sector level. For both investors and policymakers, the findings point to the value of tracking India VIX as part of risk management, portfolio construction, and market stabilization strategies.

Conclusion

The study finds that market sentiment, proxied by the India VIX, has a decisive impact on sectoral returns in the Indian equity market from 2014 to 2024. The financial services and banking sectors proved to be the most sensitive, suffering steep declines during episodes of market stress, while defensive sectors such as FMCG, Healthcare, and IT held steadier, acting as safe havens for investors. Fat tails, negative skewness, and persistent volatility indicate that market returns exhibit complex, non-normal behavior when driven by shifts in sentiment. Moreover, the two-way links between the VIX and sectoral performance point to feedback effects and timing differences, reinforcing the behavioral view that market movements are not driven by fundamentals alone.

By demonstrating how market sentiment affects sectors differently, this study highlights the importance of incorporating behavioral factors into models of market performance. For investors, the results stress the need for sector-focused risk management and diversification. For policymakers, they shed light on how shifts in sentiment can intensify volatility and add to systemic risk.

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Implications

For Investors and Portfolio Managers:

Recognizing that sectors react differently to shifts in market sentiment helps investors design more resilient portfolios. Defensive areas like FMCG, Healthcare, and IT tend to provide stability in turbulent periods, while more sensitive sectors such as Financial Services and Banks demand careful risk control. Monitoring the India VIX serves as a useful guide for adjusting positions when market stress rises.

For Financial Practitioners and Fund Managers:

Using the India VIX in forecasting and risk models can strengthen decisions on asset allocation, hedging, and volatility management. Recognizing that volatility tends to persist also supports more flexible portfolio adjustments instead of relying only on static strategies.

For Policymakers and Regulators:

Understanding how sectors respond to shifts in investor sentiment can guide targeted interventions, particularly during periods of systemic stress. Transparent communication and steady policy measures are crucial for reinforcing investor confidence and limiting disruptions caused by herding behavior.

For Behavioral Finance Research:

This study lends support to behavioral finance theories such as herding and risk aversion by showing how sentiment-driven dynamics shape sectoral returns. The two-way influences between the VIX and sector indices illustrate the interplay of market psychology and fundamentals, a pattern that is more prominent in emerging markets.

Recommendations

Portfolio Diversification: Investors should rebalance toward defensive sectors during high-volatility phases while limiting concentrated exposure to highly sensitive sectors.

Risk Management: India VIX should be adopted as an early warning indicator to guide proactive hedging and asset allocation decisions.

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Policy Guidance: Regulators can use insights from sentiment–sector linkages to design policies that stabilize markets during stress, with particular attention to sentiment-sensitive sectors like banking and financial services.

Limitations and Future Research

The study relies exclusively on India VIX as a proxy for sentiment, which, while widely accepted, may not capture all dimensions of investor psychology. Incorporating alternative sentiment measures such as social media indices, analyst forecasts, or retail trading flows could enhance robustness. Additionally, the analysis is restricted to daily data and selected econometric models; high-frequency datasets and machine learning–based sentiment forecasting could provide richer insights. Future research may also extend the framework to cross-border volatility spillovers, comparative sectoral studies across emerging economies, and the role of policy interventions in moderating sentiment-driven volatility.

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