FEAR AND FLUCTUATIONS: AN EMPIRICAL STUDY OF INVESTOR SENTIMENT AND ASYMMETRIC VOLATILITY IN INDIA

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Abstract: India's capital market represents a dynamic depiction of its economic growth and capital creation, exemplified by volatility that triggers a range of acknowledgement from investors. When making informed investment decisions, investors often consider emotional factors that influence volatility. This research explores the nexus between investor sentiment, represented by India VIX and stock return volatility. The analysis examined the dynamic relationship through the application of ordinary least squares (OLS) methods, the Granger Causality test and the Exponential Generalised Autoregressive Conditional Heteroskedasticity (EGARCH) model. The results from the EGARCH analysis indicated asymmetric volatility effects, unveiling increased volatility following negative shocks. Conditional variance results exhibit fluctuating volatility, which peaked during crises such as COVID-19, manifesting market uncertainty and risk dynamics over time. This investigation is significant for investors, policymakers, regulators and scholars, as it provides valuable insights, empirical evidence and a profound knowledge of capital market mechanisms and risk management tactics.

Keywords: Investor sentiment, EGARCH, Asymmetric Volatility, VIX

JEL Classification: C58, D53, E44

Introduction

Financial market instruments such as financial assets, market dynamics, assets pricing and return volatility etc., is largely affected by investor sentiment which is a critical driver of financial market and marketizations of these assets in a stock exchange ensures a smooth flow of capital which is scarce resource of an economy mobilizing from households to the business sector that enabling investors quick buy, sell and hold the stocks. It's referred to as investor liquidity. These two

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goals are market price mechanism aims to achieve, and it drives efficient capital allocation (Suresh, P.S., & George, S., 2016). The stock market plays a foundational role in growing, sustaining and is a key engine to the development and stability of an expanding economy. It's referred to as a cornerstone for financial progress and the effective function of the financial system in an economy (Gupta, H. (2025). Investors who are interested in knowing the volatility of return, which reflects market uncertainty and risk that is tied to their investments. This volatility in security prices is the constraint for the investors' returns, and from the company's perspective, volatility, i.e., risk, plays a key role in ascertaining financial leverage, cost of capital, and shows the right path for investment decision (Gupta, H. (2025). Investor sentiment opposes prior efficient market theories by incorporating the influence of irrational behaviour on stock volatility. It's a contrast with rational investors or Noise traders whose psychological decisions drive stock return volatility beyond what fundamental factors forecast. According to traditional finance, perfect markets and investor rationality are the assumptions of the markets by which they make investment decisions based on available market information, and market prices fully reflect current market conditions. This conventional finance concept is the basis to understand the market functions is the presumptions of many market participants (Vaswani, P., & Padmaja, M. (2025), while the behavioral finance theory prospects a different perspective where the investors are seemed to be non-rational decision maker who adopt choice based on different kind of emotions (fear, joy, sad etc.), biases, or market sentiment, which results in market anomalies (Ogunlusi and Obademi, 2019). Guo et al. (2024) in their findings mentioned that investors often consider fundamental information for making rational decisions, but a contradictory notion where stock prices change not only depend on the fundamental values but also on emotional as well as psychological factors that affect investment decisions. Investor sentiment, i.e., emotion-driven trading, can lead to undervalued or overvalued bubbles, mispricing, market inefficiency and stock panic selling and that generating excessive market volatility which is not fundamentally justified (Shiller, 2003; Ji et al., 2022). Yet, that view is challenged by behavioural finance and by investor psychology bias and mood, which indeed dominate market behaviour (Shiller, 2003). According to Baker & Wurgler (2007), collective outlook and emotions reflect investors' overall attitude towards the market. These two are acknowledged as the primary causes of stock market volatility. It is also treated as a leading gauge of risk, measuring how widely asset prices swing over time. Equity return reacts differently to equally sized positive and negative market events. This unequal response in the stock market is called asymmetrical, where bad news has more influence on return volatility than positive news. Volatility index or VIX indicates the market's implied expectations of future volatility. It also acts like a barometer of market volatility and investor sentiment. For analyzing the influence of investor sentiment on stock market behavior, VIX is one of the reliable measures as it reflects expected short-term volatility and showing a negative relationship with stock returns- low volatility index means market is optimist, and low risk where a high VIX indicates fear and projections of significant price change (Idnani et al., 2021). Considering asymmetry in volatility study is important, as markets react more to negative news than positive news. Asymmetric volatility modelling provides a better investment decision, policy implications, and effective market risk management. Ignoring this possibly led to inaccurate risk assessment, assets mispricing, and inappropriate investment decisions. The impact of it on volatility has been analysed in various cross-region tests (Da, Engelberg, & Gao, 2015; Smales, 2017). Some researchers have suggested that social media sentiment is especially informative for stock returns and volatility, while others believe that this reflects the prices of stocks because traditional economic and financial fundamentals continue to drive the markets. The Indian equity market is the fastest-growing emerging capital market in the World, providing an extensive market structure, a large investor base and vulnerability to macroeconomic and global shocks over time. Our study is important for the Indian Capital market due to growing retail investor participation, frequent global economic shocks, and uncertainties, which lead to sentiment-driven market risk that influences market stability, different categorical investment decisions, and risk-return management. This study employs VIX as a proxy of investor sentiment and examines its relationships with stock return volatility in the Indian market. The EGARCH (1,1) model is employed to detail asymmetric volatility effects. Further, Granger causality tests are escort to examine the directional relationships between return volatility and India VIX.

Literature Review

In finance, two primary frameworks- efficient market hypothesis (EMH) and behavioural finance theory give contrasting perspectives on sentiment and its impact on volatility (Shi, 2025). According to Fama, E. F. (1970), the market reflects all available information where investors are rational. Under this framework, price volatility results from the incorporation of new fundamental information like earnings reports, economic indicators, or interest rates, not from irrational behaviour or emotional reactions. Any deviations from a stock's intrinsic value are expected to be short-lived, as arbitrageurs quickly exploit and correct any mispricing. This theory, however, struggles to explain certain market phenomena, such as speculative bubbles, excessive volatility, and sudden crashes. Despite its widespread acceptance, it has been increasingly challenged in explaining real-world market behaviors, in case of financial downturn during the year 1990s bubbles, 2008 worldwide economic crisis exposed limitations of EMH, as market prices exhibited extreme volatility that could not be explained solely by new fundamental information also not always efficient and rational (Khan et al., 2024). This herding can exacerbate market trends, leading to either overvaluation (bubbles) or undervaluation (crashes) of stocks. Overconfident investors might ignore fundamental information, relying instead on personal judgments. Market sentiment emerges from heuristic behaviour, biased decisions of investors, rather than rational analysis (Suresh, P.S., & George, S., 2016). Keynes pointed out economic volatility as a consequence of psychological and social forces. During financial uncertainty market often shows herd behaviour that intensifies positive and negative sentiment, which steers market interactions and value changes.

Sentiment-driven trading, often characterised by optimism or pessimism (Andleeb, 2024). Irrational sentiments, such as panic selling or euphoric buying, can lead to excessive volatility and sharp price swings that are disconnected from actual economic or corporate performance, though results vary depending on how sentiment is measured and the time frame examined. Research shows that during positive sentiment, stock prices generally rise beyond their fundamental values, increasing the risk of a market correction. Conversely, during periods of negative sentiment, such as financial crises, markets often experience sharp declines due to panic selling and risk aversion. Baker and Wurgler (2006) developed a composite sentiment index by applying principal component analysis (PCA) methods to construct investor sentiment by taking multiple proxies. They found that high sentiment leads to increased volatility. Their research showed a stronger influence on high-growth and speculative stocks, as these stocks are more sensitive to irrational behaviour. Da, Engelberg and Gao (2015) in their study select variables to measure sentiment, such as Google search volume data, media sentiment, and news articles. They used textual analysis of daily columns and found that negative news sentiment was correlated with stock price declines and increased market volatility, also spikes in search activity predicted future stock returns and volatility. Similarly, Tetlock (2007) in his study analysed and found that negative sentiment in media reports leads to stock price declines and increased volatility. These studies highlight that sentiment-driven volatility is a persistent feature of modern financial markets. Despite these advances, there remains a lack of consensus on the structural aspects of investor sentiment, particularly on how to distinguish between rational and irrational sentiments. While several sentimental indices have been developed, many fail to capture the deeper psychological factors driving irrational behaviour. Additionally, most existing studies focus on aggregate market sentiment without distinguishing its varying effects across different market conditions, such as financial crises or speculative bubbles. Our study focuses on addressing these gaps by taking a sentiment proxy as India VIX and its effects on return volatility using GARCH, EGARCH and Granger causality frameworks. This study selects VIX as a proxy of investor sentiment that measures market expectations of volatility, which is often reflected as a fear gauge; the higher the VIX, indicates higher the uncertainty and market pessimism (Whaley, 2000; Baker et al., 2016). Sardar, A., & Khan, G. S. (2024), in their study, examine the stock return and investor sentiment link by employing different econometrics. They have taken ten years of data on the NSE Nifty fifty close price and taken market-based proxies to construct a sentiment index. Researchers found that the short-term impact of sentiment on stock return also unidirectionally causes. Many empirical studies found that VIX correlates with volatility and market downturns, which is driven by investors' panic selling and fear. More recent studies have shown the relationships among VIX as a proxy of investor sentiment and return volatility. Smales (2017) examines this relationship and found that the VIX can effectively impact sentiment, especially during a crisis where investor fear drives a large scale of market interruptions. He also put the point of investors' psychological behaviour, like overconfidence, herding, etc., that leads to uncertainty in stock prices, causes excess volatility in the market, particularly during the specific period of bubbles, dot.com. Brown and Cliff (2004) studied a select consumer sentiment index, considered a good predictor of return and volatility. Their findings showed that optimism and pessimism are investors' sentiment, which deviates from market fundamental factors that lead to excess market volatility. Authors started selecting different proxies to measure sentiment, and the rise of social media has also been used to assess the positive and negative attitudes of stakeholders. (Chen et al., 2014) investigated Twitter sentiment and market movements. They found stock price declines due to increased negative sentiment on social media. (Phan & Narayan, 2020) examines the impact of investor sentiment during the COVID-19 pandemic on markets across G20 countries. They found that both positive and negative sentiments influence return volatility. Panel VAR model methodology was used in their study to capture the dynamic relationships among them. Another study developed by Cheng and Liu (2005), using proxies such as Google search volumes, survey-based variables for constructing a sentiment index by assuming that it may act as a predictive factor for stock returns with a remarkable impact on volatility because it's closely tied to risk aversion and anomalies. Some studies use news sentiment articles and investigate their impact on stock volatility. A study using econometrics methodology, like ARCH and GARCH models, found that news sentiment significantly contributes to market volatility, especially during periods of heightened uncertainty. The study also exposes the asymmetrical response of markets to positive and negative news. These studies support the notion that investor sentiment, particularly irrational sentiment, significantly contributes to stock market volatility. According to Uygur and Taº (2014), the influence of sentiment traders during the high sentiment period is more than during the low sentiment period, referred to as the theory of noise traders. They employed EGARCH to understand the influence of earnings shocks on conditional volatility in a high sentiment period. The study found asymmetric fluctuations in international market indexes. Market risk is referred to as a potential loss that is assumed to be caused by the effects of macroeconomic factors like interest rates, inflation, money supply, financial policy and uncertainty. A geopolitical crisis is the reason for market risk. affects the overall performance of financial assets. Such a broad economic information is the cause of investors' rational response towards the market (Vaswani, P., & Padmaja, M., 2025). This concept is often challenged by the behavioural finance theory. Moreover, the fluctuations of macroeconomic factors in moulding the sentiment-volatility interconnections study in India remain insufficiently explored phases. Therefore, this study endeavours to address these gaps by giving an extensive analysis of investor sentiment (India VIX) and its interactive connection with return volatility in the Indian capital market.

The emerging country, like the Indian economy, has shown its transformational journey since 1991, yet there is unequal information access, investor heterogeneity, arbitrage limits, and the involvement of market intermediaries still visible. It is very crucial to determine how sentiment impacts market return and volatility (Suresh, P.S., & George, S., 2016). Understanding the crucial role of investor sentiment driving volatility has important implications for policy makers, investors and regulators, to mitigate risk and stabilise policy. Prior studies aggregate different market related proxies to construct sentiment index or largely concentrates on overarching sentiment proxy like media based, news sentiment fairly on market-based indicator such as India VIX instead this research aims to investigates the impact of sentiment on return volatility where it considers VIX as proxy of sentiment also employed different econometrics model to find out the relationships between them. While wide-ranging of research relating to this topic exists in the developed market, relatively few researchers have explored this phenomenon in emerging markets like the Indian equity market. However, previous studies used econometrics more on linear models, but this study uses the EGARCH model to capture the phases (positive or negative sentiment) of investor sentiment, i.e., asymmetric effects on volatility, conditional variance, Granger causality test, etc. So, a notable research gap in Indian studies associating Investor sentiment and asymmetric volatility using VIX, specifying the essentiality of the study that apprehends the ascendancy of behavioural finance.

Methods

This section discusses the variables and methodology that have been used to conduct the research. In terms of stock market return, we select the National Stock Exchange Nifty 50 monthly closing price data, collect monthly data from April 2013 to March 2023 from an official website and to calculate the return of a selected index, the steps are as follows:

Return = $\ln\left(\frac{Pt}{Pt-1}\right)$*100 (Hu, J., Sui, Y., & Ma, F,2021; Paramanik, R. N., & Singhal, V., 2020).

Where Pt is the current month's price and Pt-1 is just the previous month's price, where a positive return signifies a bullish trend and a negative return signifies a bearish trend in the market. Several studies authenticate the use of VIX in sentiment measurements (Smales, 2017); Anamika, Chakraborty, M., & Subramaniam, S, 2023; Reis, P. M. N., & Pinho, C., 2021. This paper has also taken India VIX as a proxy of Investor sentiments, which is considered as a dynamic measure of sentiment that provides insights into risk perceptions and behavioural biases, where high VIX indicate uncertainty and fear, and low VIX (bullish sentiment) denotes confidence and stability among investors (Sinha, A., & Mandal, S. K., 2021). Reis, P. M. N., and Pinho, C. (2021) find a direct relationship between investor sentiment with investor psychology. The reasons behind this selection are that VIX is a reliable measure of fear or overconfidence (Shaikh, I., & Huynh, T. L. D., 2022). According to Roszyk, N., and lepaczuk, R. (2024), VIX is an important measure that helps to assess market risk. They incorporate daily data of the S&P 500 and VIX index data spanning the period from 2000 to 2023. Researchers employed the GARCH model, LSTM network, and hybrid LSTM-GARCH to evaluate market sentiment. They found machine learning approach (hybrid LSTM model) surpasses the traditional GARCH model, which enhances the predictive ability.

The stock market is often considered a barometer of the economy. Macroeconomic determinants such as Gross Domestic Product, inflation, interest rate, foreign exchange rate, foreign direct investment, foreign portfolio investment, T-bills, etc., significantly affect investor behaviour (Sorokina, 2013). Therefore, this study used macroeconomic variables such as the index of industrial production, exchange rate, T-bills, foreign institutional investment, wholesale price index, etc., to measure the intensity of investor sentiment on return volatility (PH &Rishad, 2020).

Empirical Results

Table 1 of the descriptive study reveals the distribution, variability, and normalcy of return (RT) and VIX. A small average positive mean return is 0.9026, and a near-symmetric distribution is suggested by the median return of 0.9280. By comparison, the average market volatility index level, or VIX, has a mean of 17.86. Returns are more variable than VIX values concerning their means, as indicated by the standard deviations (RT: 4.8659, VIX: 6.26). Extremely negative returns happen more frequently than positive ones, as seen by the left-skewed distribution indicated by the skewness of RT, which is -1.2421. With a high positive skewness (3.85), the VIX indicates a lengthy right tail, which indicates sporadic, sharp increases in market volatility. Heavy-tailed behaviour is indicated by kurtosis values (RT: 10.1119, VIX: 27.02) exceeding 3, demonstrating frequent extreme values and heavy-tailed distributions. With p-values of 0, the Jarque-Bera test results (RT: 281.39, VIX: 3182.35) verify that both distributions exhibit a considerable departure from normalcy. When choosing suitable econometric models for additional.

Table 1: Summary Statistics

	RT	VIX
Mean	0.902602	17.86
Median	0.927996	16.62
Max	13.69755	64.41
Min	-26.4569	10.86
Std. Dev.	4.865937	6.26
Skewness	-1.2421	3.85
Kurtosis	10.11195	27.02
Jarque-Bera	281.3908	3182.354
Prob.	0	0
Sum.	107.4096	2143.440
Sum Sq. Dev.	2793.926	4666.649

Source: The Authors' calculation

T-bills, FPI, WPI, IIP, EXRT & VIX are some of the important macroeconomic and market-based variables that are evaluated by the regression model in Table 2. According to Wooldridge, J. M. (2002), Regression analysis is an important statistical tool used to examine the relationships between a dependent and one or more independent variables. It assists researchers in estimating or predicting the causal relationships between the variables. Furthermore, Linear regression is a widely used econometrics tool due to its simplicity, understandability and interpretability (Neter et al., 1983). At the 1% level, the VIX coefficient is -0.18, and the p-value (0.00) denotes substantial statistical significance. According to this negative coefficient, stock returns decrease as market volatility rises, which is according to the financial theory, increased volatility frequently denotes uncertainty and prompts investors to seek larger risk premiums or move toward safer assets. The highly significant p-value (0.00), the coefficient for FII of 0.00 indicates that foreign capital inflows have a favourable impact on stock performance. This is to be expected since FII inflows increase stock prices, investor confidence, and market liquidity. It has a significant impact, where t-statistics (7.27), but the p-value is not statistically significant, despite the coefficient being -0.09, suggesting that changes in industrial production have little effect on stock returns during the studied time frame. Transmission delays or other powerful market pressures may be to blame for this. The high p-value (0.96) and coefficient (-0.01) indicate returns are not significantly influenced by changes in the exchange rate. This implies that other macroeconomic factors either control the behaviour of the market or are resistant to changes in exchange rates. Although TBILLS is not statistically significant (p = 0.37), which represents short-term interest rate movements, it does not directly affect stock returns. A WPI value represents a positive correlation between stock returns and inflation. The p-value (0.24) is not statistically significant, nevertheless. The overall impact of inflation on stock returns is yet unknown, and it may have varying effects on different industries. R-squared shows the statistical significance of the entire model, attests to the substantial influence of at least one independent variable on stock returns. This suggests that the model is reasonably resilient because there isn't any significant autocorrelation in the residuals. This implies that foreign capital flows and sentiment, as assessed by the VIX, are the main factors influencing market movements. To further improve the study, future studies should include nonlinear effects or interactions between these variables.

Table 2: Regression Analysis

Dependent variable: Return

Method: Least Squares

Variable	Coefficient		t-Statistics	Prob.
VIX	-0.18	0.06	-2.91	0.00
IIP	-0.09	0.13	-0.64	0.52
EXRT	-0.01	0.17	-0.05	0.96
TBILLS	-0.52	0.58	-0.89	0.37
FII	0.00	0.00	7.27	0.00
WPI	0.13	0.11	1.18	0.24
C	-2.19	12.63	-0.17	0.86

Source: The Authors' calculation

Unit Root Test

Table 3 shows the stationarity test, which is used in this research to determine whether the time series data is stationary or non-stationary. It's necessary to have trustworthy and objective estimators. Finding this feature is crucial for time series analysis, particularly for hypothesis testing and econometric modelling. A stationary test of the variables is necessary to ensure consistent, dependable forecasting and prevent misleading results (Gorodnichenko, Mikusheva and Ng, 2012). We utilised the most popular augmented Dickey-Fuller test (ADF) to determine whether each variable's time series attributes had a unit root. The stationarity of both VIX and RETURN is confirmed by the results which were performed using trend and intercept, verified the stationarity of both VIX and RETURN using trend and intercept. The alternative hypothesis proposes stationarity, whereas the null hypothesis asserts that the series is non-stationary. The VIX (-5.9269), return (-11.2511) t-values in this instance are all extremely negative, and their p-values are zero, which is below any typical significance level (1%, 5%, or 10%). We conclude that both series are stationary at their levels, and the null hypothesis is rejected since the p-values are statistically significant. These findings validate that VIX and RETURN can be employed directly in additional time series modelling without differencing, which is a critical prerequisite for many econometric models, including VAR, GARCH, and cointegration analysis. As a result, any further statistical conclusions and model estimations based on these variables are more reliable.

Table 3: Stationary Test

Variable	t-Value	P-Value
VIX	-5.8489	0
RETURN	-11.2511	0

Source: The Authors' calculation

According to Brandt, M. W., & Jones, C. S. (2006), the characteristics of return volatility clustering, inverse relationships with returns, log normal distribution, etc., are effectively encapsulated by the EGARCH model. Over time, this model has been recommended by many researchers, Nelson (1989,1991), Pagan and Schwert (1990), Engle and Lee (1991). The EGARCH model can capture the oscillation of log return (Nelson, D.B. 1991). Table 4 estimates the EGARCH result, where the mean equation's constant term, 0.8503, has a p-value of 0.0541, making it marginally significant, which means a modest positive mean return during the study period. The lack of ARMA words suggests that historical returns have little bearing on present returns. P-value = 0.0000; Cst(V) = 2.9423:

This is very large and indicates the base level of conditional variance, suggesting a high intrinsic level of market volatility. ARCH (Alpha1) = -0.2376 (p-value = 0.6888) quantifies the impact of previous shocks on the volatility of the present. This coefficient indicates that current shocks have little effect on market volatility because it is negative and statistically insignificant. (p-value = 0.1377) GARCH (Beta1) = 0.5008, the volatility's persistence is captured by the GARCH component. A coefficient of 0.50 suggests that volatility shocks do endure, albeit not significantly, even though it is not statistically significant. The capacity of EGARCH to capture volatility asymmetry is one of its main advantages over conventional GARCH models. -0.4617 (p-value = 0.0056) EGARCH (Theta1): Given that it is negative and extremely important, this is a crucial result. It implies that volatility is raised more by negative shocks (bad news) than by positive shocks (good news) of the same size. This is frequently seen in financial markets and is referred to as the leverage effect. The magnitude effect is captured by the term EGARCH (Theta2) = 0.3921 (p-value = 0.1400), which indicates that volatility is influenced by the absolute size of shocks. It implies that volatility is not significantly impacted by return magnitude, though, as it is statistically insignificant.

Table 4: Estimated EGARCH model

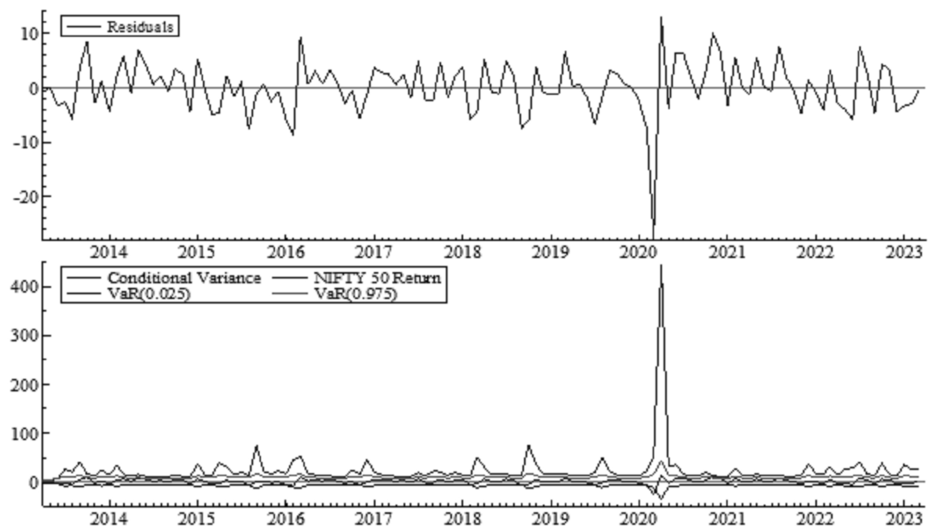
Parameter	Coefficient	Standard Error	t-value	p-value
Cst (Mean Equation)	0.8503	0.4369	1.946	0.0541
Cst (Variance Equation)	2.9423	0.2118	13.89	0.0000
ARCH (Alpha1)	-0.2376	0.5918	-0.4015	0.6888
GARCH (Beta1)	0.5008	0.3350	1.495	0.1377
EGARCH (Theta 1)	-0.4617	0.1636	-2.821	0.0056
EGARCH (Theta 2)	0.3921	0.2638	1.486	0.1400

Source: The Authors' calculation

Conditional Volatility

Figure 1 provides crucial information regarding the risk dynamics and volatility, and the proper knowledge of the market. Important information about the volatility and risk dynamics of the Indian equity market may be gained from the conditional variance analysis of the NIFTY50 index over time, shown in Figure 1, particularly in response to market circumstances and economic events, which requires knowledge of conditional variance, which quantifies the variability of returns given historical information. The conditional variance data for 2014 probably showed low volatility, which was indicative of a time when the Indian market was recovering from international financial worries and was comparatively stable. However, major domestic events like demonetization, which created short-term economic disruptions and market anxiety, may have contributed to the heightened volatility in later years, especially around 2016. As the market adapted to new economic policies and conflicts in international commerce, 2017 and 2018 may have seen varying conditional variations. The pandemic (COVID-19), which produced unmatched global market volatility, would have had a huge impact on the conditional variance in 2019 and 2020. In 2021 & 2022, when the market started to revive, consequently, variance gradually declined and projected to a more stable market condition. Aftermath of the pandemic, along with geopolitical unrest and inflationary pressure, volatility at a given threshold and steady market situations stabilise by 2023.

Figure 1 Conditional Variance



Granger Causality Test

Granger is a popular analytical tool for time series data in econometrics, finance, neuroscience and other applied domains. It refers to a causality that, based on past values of a time series able to predict another series' future values (Shojaie, A., & Fox, E. B., 2022). The pairwise Granger causality is shown in Table 5, which creates a unidirectional causal link between VIX and return volatility. The p-value in the given table is less than 0.05, which strongly rejects the hypothesis that Granger-cause volatility strongly rejected. The result suggests that the historical Vix values significantly predict return volatility. Other results show the p-value is more than 0.05, and low F-statistics imply volatility cannot predict VIX, which is more than just responding to previous market swings and is treated as one of the prime indicators of market volatility. According to earlier research, VIX is considered a market fear that captures investor sentiment and expectations for future uncertainty (Corrado, C. J., & Truong, C., 2008). Beyond historical volatility metrics, options-implied volatility measures appear to have valuable information regarding future market changes due to the great predictive potential of VIX on RT_VOLATILITY (Christensen and Prabhala, 1998). Practically speaking, these findings have significant ramifications for traders, investors, and legislators. The VIX is a risk management tool that market participants can use to hedge against expected volatility spikes by incorporating it into trading strategies. Using VIX as a forecasting variable may also help portfolio managers dynamically modify risk exposure. In addition, central banks and policymakers can keep an eye on VIX levels as a measure of financial stability, which enables them to take preventative action when market stress is at its highest (Diebold and Yilmaz, 2012). Overall, the results support VIX's well-established predictive function. Overall, the results show that there is no reverse causality between realised volatility and market expectations, supporting VIX's well-established function as a predictor of market turmoil. To better understand volatility dynamics, future research may expand this approach by adding additional macroeconomic factors and investor sentiment indexes.

Table 5: Pairwise Granger Causality Test

Null Hypothesis	**Obs**	**F-Stat**	**Prob.**
VIX does not Granger-cause volatility	116	85.1077	3.92E-23
Return volatility does not Granger-cause VIX	0.32258	0.72495	

Source: The Authors' calculation

Conclusion

The study conducts a comprehensive investigation of the relationships between investor sentiment affects the volatility of stock market returns. The NSE Nifty50 monthly closing price consideration from April 2013 to March 2023 was taken as a representative of the Indian equity market. Return volatility is calculated using the GARCH (1,1) approach. Granger causality was also used to investigate the connection between volatility and investor mood. Macroeconomic fundamentals like the index of industrial production, exchange rate, treasury bills, foreign institutional investments, and the wholesale price index that regress with the return. The OLS, GARCH, EGARCH (1,1) model and Granger causality regression techniques were used in the investigation. The outcome of this empirical research provides valuable findings. It is observed that OLS results highlighting the diverse effects of macroeconomic variables on market performance, like foreign institutional investments (FII), have a positive influence on stock returns, while volatility negatively impacts them. The EGARCH (1,1) model, which the study revealed to have an asymmetrical connection, shows a strong leverage effect, i.e., a negative news impact than a positive news impact. According to these findings, bad news causes more market volatility than good news of the same size because it raises the risk premium, increases uncertainty, and may trigger sell-offs. Investors' reactions to negative news, events, etc., cause the market to fluctuate more. Conditional variance analysis, which the study also discovered, indicates time of increased volatility brought on by significant economic developments, such as demonetization (2016), COVID-19 (2020), and geopolitical concerns. Even though volatility decreased after 2021, market stability is still impacted by lingering impacts and policy changes. VIX predicts future volatility, according to the Granger causality conclusion, which shows a unidirectional causal relationship between VIX and RT_VOLATILITY. However, VIX is a leading indicator of market instability, and RT_VOLATILITY does not Granger-cause it. According to the study, investor mood and economic shocks are the prime causes of market volatility in India. The study highlights the importance of strong risk management and VIX-based volatility forecasting techniques.

The above findings carry important policy implications for the market participants, policy makers and market regulators. Firstly, they should prefer to enhance the risk management framework and also promote to application VIX VIX-based forecasting tool for measuring sentiment. Secondly, by identifying the influence of investor sentiment and asymmetric volatility, that assessment enhances transparency of the market as well as investor financial literacy, which can assist in market stabilisations and hedge against the two negative financial shocks. The findings also provide insight into how investor mood, a non-fundamental factor, drives the Indian equity market and shapes the risk and return perception of investors, which in turn supports behavioural theories on the capital market. Asymmetric volatility and a sizable leverage effect indicate that markets do not just follow a random walk. Retail investors, policymakers, qualified institutional buyers, institutional investors, and other decision-makers in the Indian capital market may find value in the study's conclusions.

The limitations of this study are that it only considers the Indian market. The results, however, are restricted to monthly data and a small number of sentiment proxies. Therefore, future research suggests adding more proxies, including daily data of more stock market indices across various continents, and other machine learning techniques for constructing the sentiment index could expand the study, increase its value, also facilitate obtaining more precise and comprehensive insights within the global markets.

Conflict of Interests

The authors declare that there is no conflict of interests that are directly or indirectly related to this research work.

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