

Does investor sentiment affect futures market volatility? Evidence from the Indian index futures market

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Abstract

Purpose – This study investigates the impact of investor sentiments on the volatility of the Indian Index Futures market. Furthermore, this study examines whether the futures market exhibits spillover effects between sentiment and volatility.

Design/methodology/approach – A sentiment index is constructed using PCA to capture investor sentiment, and it is incorporated into the mean and variance framework of the GARCH (1,1) and EGARCH models to capture investor sentiment in the futures market. The Diagonal BEKK GARCH Model analyses the spillover effect between sentiment and volatility in the Indian Index futures market.

Findings – The GARCH(1,1) results confirm a significant impact of investor sentiment on futures market volatility, with strong volatility persistence. The EGARCH results confirm a significant investor sentiment effect on the volatility with a leverage effect, indicating that negative shocks impact volatility more than positive shocks. The Diagonal BEKK GARCH results reveal significant bidirectional sentiment volatility spillover in the Indian Index Futures Market.

Originality/value – This study makes an original contribution by extending investor sentiment research to the Indian index futures market, an area that has received limited empirical attention. This study provides evidence that investor sentiment significantly influences futures returns, volatility, asymmetric volatility and bidirectional spillovers. By demonstrating the leverage effect of negative news and the dynamic interaction between sentiment and market volatility, the study offers valuable behavioural insights with practical implications for volatility forecasting, market surveillance, regulatory policy and financial stability in emerging derivatives markets.

Keywords Volatility, Spillover effect, Investor sentiments, Index futures market, GARCH models

Paper type Research article

1. Introduction

The well-known efficient market theory explains the presence of an efficient market and rational investors (Fama, 1970), broken by market crashes like Black Monday on 19th October 1987. Furthermore, the presence of market anomalies like the day-of-week effect, January effect and Market bubbles contradicts the belief of EMH by providing strong evidence of irrational trading in the stock market (French, 1980; Kumar & Jawa, 2017). Impulsive decisions of investors based on their bias and emotions drive the price away from its fundamental value, which creates huge volatility, and their herding tendency and aggressive buying with high return expectations result in market crashes (Summers, 1986; De Long, Shleifer, Summers, & Waldmann, 1990; Shleifer & Summers, 1990; Chen, Kim, Nofsinger, & Rui, 2007; Zhang, Bissoondoyal-Bheenick, & Zhong, 2023; Goodell, Kumar, Rao, & Verma, 2023). The market anomalies and volatility have drawn the attention of researchers and led to the development of behavioural finance, which incorporates psychological theories to study investor behaviour. Behavioural Finance theories explain that investor sentiment or emotion

JEL Classification — C22, G11, G12, G13

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significantly affects stock market volatility (De Long, Shleifer, Summers, & Waldmann, 1989; Shleifer & Summers, 1990; Thorp, 2004; Brown & Cliff, 2004; Baker & Wurgler, 2006).

Most of the existing Indian literature in this field focuses on the impact of investor sentiment on the volatility of equity markets (Kumari & Mahakud, 2015; Naik & Padhi, 2016; Aggarwal, 2017; Haritha & Rishad, 2020; Kamath, Shenoy, Abhilash, & Kumar, 2024). However, the impact of investor sentiment on the futures market volatility is less explored (Yang & Gao, 2014; Li & Liu, 2021; Chen, Bao, & Jin, 2021, 2022; Ryu & Yu, 2022; Li, Liu, & He, 2025). In emerging markets such as the Indian futures market, no studies investigating the impact of sentiment on index futures were found. Investors use futures markets for hedging to mitigate losses and for speculation to earn profits, which increases the need to investigate the impact of sentiment on the futures market. Hence, this study tries to fill this gap by investigating the effect of investor sentiment on the Indian Index futures market.

This study provides some insightful contributions to the existing literature. First, this study examines the sentiment impact on the Indian futures market, which has not been adequately examined. Second, in this study, the first two principal components are used to construct the sentiment index to capture the maximum information content, a novel approach compared to the proposition of Baker and Wurgler (2006) of taking only the first component for sentiment development. Third, this study investigates whether a spillover effect exists between sentiment changes and volatility in the Indian futures market, an issue that has not been explored yet. Fourth, this study uses daily data on near-month futures contracts, as the futures life cycle is short and investor sentiment effects cannot be identified from monthly data (Li & Liu, 2021). Fifth, this study employs the India VIX, termed the fear index, as a proxy for sentiment index development, helping incorporate changes in investor sentiment driven by market volatility into our sentiment index.

The rest of the article is organised as follows: Section 2 explains the Literature Review; Section 3 outlines the Data and Methodology; Section 4 reports the results and findings; Section 5 offers a discussion; Section 6 concludes the study and Section 7 highlights the implications, limitations and future research.

2. Literature review

The existing behavioural finance literature explained the irrationality of investors that created mispricing and volatility in the market. They confirmed the presence of emotions and biases in investor decisions that create havoc in the stock market (Summers, 1986; De Long *et al.*, 1989; Shleifer & Summers, 1990; Cevik, Kirci Altinkeski, Cevik, & Dibooglu, 2022). In-depth studies in this field proved that investor sentiment is the emotion or attitude of investors, which is a significant factor that determines his/her investment decision (De Long *et al.*, 1989; Thorp, 2004; Brown & Cliff, 2004; Baker & Wurgler, 2006; Li & Liu, 2021; Masood, 2024). Trading decisions driven by emotions and biases create irrationality and overreaction, leading to market price fluctuations (Kumari, 2025; Singh & Dixit, 2025). If most market participants blindly follow this irrational behaviour, it will create volatility and market crashes (De Long *et al.*, 1989, 1990; Shleifer & Summers, 1990; Naik & Padhi, 2016). Studies on the impact of investor sentiment on the Indian Stock Market revealed that irrational investor sentiment has a significant asymmetric impact on volatility, indicating that negative shocks or news have a greater impact than positive news (Kumari & Mahakud, 2015; Naik & Padhi, 2016; Haritha & Rishad, 2020; Naik & Soni, 2026).

Extensive studies of the Indian futures market found that introducing index futures trading reduced volatility in the spot market (Gupta, 2002; Raju & Karande, 2004). High volatility in the spot market encourages investors to utilise the futures market as a hedging mechanism to reduce potential losses (Huang & Xiong, 2023; Krishnan, 2023; Alshammari & Obeid, 2023). Investor optimism, driven by emotional expectations of reducing losses through futures hedging, emphasises the need to examine the influence of investor sentiment on the futures market. Research on the Indian futures market has revealed a significant asymmetric effect,

indicating that negative news has more impact on volatility than positive news (Gupta & Singh, 2009; Chandra Pati & Rajiv, 2010). Recent studies in the futures market focus attention on the investor sentiment, since it has a significant impact on the returns, volatility and mispricing (Chen *et al.*, 2021, 2022; Li & Liu, 2021; Ryu, Ryu, & Yang, 2023; Ryu, Ryu, & Yang, 2025; Bahloul & Dammak, 2025). Studies on the impact of investor sentiment on the Chinese futures market revealed that sentiment significantly affects volatility, and including sentiment in the models improves the volatility prediction power (Chen *et al.*, 2021). A significant sentiment volatility spillover effect was found in the Chinese futures market (Li & Liu, 2021), proving the importance of analysing investor sentiment impact on the futures market volatility. In volatile futures markets, the sentiment-mispricing relation intensifies, and mispricing increases due to constraints on perfect arbitrage (Ryu *et al.*, 2025). Literature on the sentiment impact on futures market volatility is available globally. However, studies on emerging futures markets like the Indian futures market have not been explored adequately. This study tries to fill this gap by formulating the following research hypotheses.

- H1.* Investor sentiment has a significant effect on the returns and volatility in the Indian Index futures market.

Studies revealed that volatility asymmetry, or the leverage effect, is present in the futures market, indicating that negative news has a more significant effect on volatility than positive news, and that pessimistic sentiment is positively related to volatility (Gupta & Singh, 2009; Chandra Pati & Rajiv, 2010; Chen *et al.*, 2021). The pronounced impact of negative news in generating substantial volatility underscores the need to examine whether a leverage effect exists in the Indian index futures market and the extent to which investor sentiment influences it. To determine this relationship, we formulated the following hypothesis:

- H2.* Investor sentiment has a significant effect on the volatility asymmetry of the Indian Index Futures Market.

Studies also confirmed that a significant spillover effect is present between investor sentiment and futures market volatility, indicating that the rapid flow of information regarding the sentiment change has a significant effect on Chinese futures market returns and volatility (Li & Liu, 2021). This result underscores the importance of identifying whether a significant sentiment and returns/volatility spillover effect is present in the Indian index futures market. To analyse this we formulated a hypothesis:

- H3.* A significant spillover effect is present between investor sentiment and Indian index futures market returns and volatility.

The existing literature on investor sentiment in the spot and futures markets confirms a significant effect on volatility and other market imperfections, underscoring the need for substantial involvement by regulators and policymakers to address this issue. Evidence from the Indian spot market confirms that investor sentiment significantly influences market volatility and stability. Kumari and Mahakud (2016) and Haritha and Rishad (2020) found that sentiment-driven trading amplifies market volatility, intensifies volatility clustering and reduces market efficiency, implying that behavioural factors should be incorporated into asset pricing, risk management and market surveillance. Their findings further suggest that policymakers, regulators and market practitioners should monitor investor sentiment as an important indicator of financial market risk. Similar evidence from developed markets reinforces these conclusions. Zhang *et al.* (2023) showed that investor sentiment contributes to persistent market anomalies in Australia. These findings indicate that investor sentiment causes significant distortions in both emerging and developed financial markets, underscoring the need for policymakers and regulators to monitor it to improve market stability, strengthen regulatory oversight and support better investment and risk management decisions.

The literature on the futures market also provides similar evidence. Yang and Gao (2014) found that investor sentiment significantly influences Chinese stock index futures across

different contract maturities, with stronger effects in short-term contracts, indicating that sentiment affects not only futures prices but also pricing efficiency, hedging effectiveness and the price discovery process in futures markets. [Gao and Yang \(2018\)](#) confirmed that investor trading behaviour in the Chinese futures market is driven more by investor sentiment than by fundamental information, with both optimistic and pessimistic sentiment promoting speculative trading, increasing price fluctuations and market volatility, weakening market efficiency and highlighting the need for regulatory monitoring to curb excessive speculation. [Li and Liu \(2021\)](#) developed a sentiment-style index for the Chinese index futures market and corroborated that investor sentiment significantly influences futures returns and overall market dynamics beyond conventional economic fundamentals, indicating that sentiment contains valuable information for explaining market behaviour and that incorporating sentiment indicators into analytical frameworks can enhance trading decisions and improve risk management for exchanges and institutional investors. [Chen et al. \(2021\)](#) examined China's energy futures markets and found that investor sentiment significantly improves volatility predictability beyond traditional market variables, demonstrating that sentiment-driven trading increases market uncertainty, particularly during periods of heightened volatility, thereby establishing investor sentiment as an important risk indicator whose incorporation into volatility forecasting models can enhance risk management and strengthen market surveillance for investors and regulators. [Chen et al. \(2022\)](#) extended this evidence by demonstrating that cross-market investor sentiment in Chinese energy futures markets propagates across related futures contracts, strengthening return comovements and transmitting sentiment shocks beyond individual markets, thereby increasing systemic risk and financial contagion during periods of market stress and highlighting the importance of monitoring investor sentiment for policymakers and regulators.

Recent evidence further reinforces the importance of investor sentiment in futures markets. [Li et al. \(2025\)](#) found that investor sentiment significantly predicts returns in Chinese agricultural futures markets, with sentiment-driven trading causing temporary deviations from fundamental values and reducing market efficiency in the short run, suggesting that behavioural factors should be incorporated into investment strategies and market regulation. Similarly, [Ryu and Yu \(2022\)](#) reported that pessimistic investor sentiment amplifies the adverse effects of funding liquidity shocks on futures market liquidity, increasing liquidity risk and reducing market resilience during periods of financial stress. Extending this evidence, [Ryu et al. \(2023\)](#) showed that excessive optimism and pessimism lead to persistent futures market mispricing, weakening pricing efficiency and the price discovery process, while their subsequent study ([Ryu et al., 2025](#)) demonstrated that such sentiment-induced mispricing persists because market frictions and limited arbitrage delay the correction of pricing inefficiencies.

Overall, international evidence demonstrates that investor sentiment has significant effects on futures and financial markets by influencing volatility, market efficiency, price discovery, liquidity and pricing behaviour. Studies from China, India and Australian markets show that sentiment-driven trading can create market distortions and increase financial risk, highlighting the importance of monitoring investor sentiment for policymakers, regulators, exchanges and investors to strengthen market surveillance, improve risk management and maintain financial stability. Despite the growing body of international evidence, there is a shortage of comprehensive studies examining the impact of investor sentiment on volatility in the Indian index futures market, as most existing Indian literature focuses primarily on the spot market. This gap underscores the need to investigate whether investor sentiment significantly affects Indian futures market volatility and to evaluate its implications for market participants, regulators and policymakers.

In the literature, several market-based indicators are widely employed as proxies for investor sentiment due to their strong theoretical foundations and empirical validation. Most of the literature on investor sentiment uses index construction based on principal component analysis of sentiment proxies to investigate the sentiment effect. Studies on volatility that incorporate

trading volume as a liquidity measure show that trading volume and volatility are positively related, indicating that higher trading volume increases futures market volatility (Bessembinder & Seguin, 1993; Wang & Yau, 2000; Chan, Fung, & Leung, 2004). Literature used trading volume and turnover as liquidity measures, indicating that higher activity reflects increased investor participation and optimism, while lower levels indicate pessimism or uncertainty (Kumari & Mahakud, 2015; Haritha & Rishad, 2020; Li & Liu, 2021; Sen, Kazmi, Mohan, & Ashhar, 2025). Similar findings were reported in studies of the Indian futures market, which showed that, as a liquidity measure, open interest and volatility were negatively correlated, whereas trading volume and volatility were positively correlated (Chandra Pati & Rajib, 2010; Pati, 2008). Researchers also used the Volatility Index, Market Mood Index, Relative Strength Index (RSI) and the Put-Call ratio as sentiment proxies to measure the investor reaction and sentiment effect in the market. The Volatility Index, as a fear indicator, reflects market expectations of near-term uncertainty, which is directly linked to fear and risk perception (Aggarwal, 2017; Mutum, 2020; Abraham & Kurian, 2022; Stivers & Bansal, 2025; Negi, Kushwah, Jaiswal, & Rekunenko, 2025). The Market Mood Index is an indicator of investor sentiment that quantifies the prevailing emotional state of the financial market, ranging from extreme fear to extreme greed (Aggarwal, 2017; Abraham & Kurian, 2022; Negi et al., 2025).

The RSI is a measure that reflects overbought or oversold conditions and captures overreactions and behavioural biases of investors while trading in a market (Chen et al., 2021, 2022). The Put-Call ratio captures market expectations and sentiment by comparing the trade volume of put and call options, with a higher PCR indicating bearish sentiment (Brown & Cliff, 2004; Kumari & Mahakud, 2015; Naik & Padhi, 2016).

Collectively, these proxies are well-established in prior studies as effective measures of investor sentiment, capturing different dimensions of market psychology and behaviour through observable market variables.

3. Data and methodology

3.1 Data

This study focuses on the impact of investor sentiments on the Indian index futures market. For the analysis, daily closing prices of the Nifty 50 futures index from 1 January 2017 to 29 December 2023 are collected from the NSE official website. Daily returns are calculated as follows:

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

3.2 Sentiment proxies

We developed a sentiment index by using seven proxies obtained from the existing literature (Brown & Cliff, 2004; Baker & Wurgler, 2006; Baker, Wurgler, & Yuan, 2012; Kumari & Mahakud, 2015, 2016; Naik & Padhi, 2016; Aggarwal, 2017; Haritha & Rishad, 2020; Mutum, 2020; Yang & Gao, 2014; Gao & Yang, 2018; Chen et al., 2021; Li & Liu, 2021). The sentiment proxies are:

Open Interest (OI): It is the total number of outstanding futures contracts that have not been settled. An increase (decrease) in OI indicates that both the short and long sides are opening (leaving) positions, and investors are increasingly (less) interested in this contract, with high (low) investor sentiment (Chen et al., 2021).

Volatility Index (VIX): It shows how much volatility or variation the Nifty 50 index will experience over the following 30 days. A higher VIX value means that the Nifty is expected to be more volatile and vice versa. Returns and VIX show an inverse relationship (Aggarwal, 2017; Mutum, 2020; Ding, Mazouz, & Wang, 2021; Abraham & Kurian, 2022; Stivers & Bansal, 2025).

Market Mood Index (MMI): It indicates the present mood of the market. The components are weighted equally and standardised to create the index on a 0–100 scale. Returns and MMI show a positive relationship (Aggarwal, 2017; Abraham & Kurian, 2022; Negi et al., 2025).

Relative Strength Index: RSI is an index that reflects whether the target market is overbought or oversold. 14-day RSI is taken as a proxy because investors use it in the market (Gao & Yang, 2018; Chen *et al.*, 2021, 2022).

Put Call Ratio (PCR): It indicates the ratio of total trading volume of put options to the trading volume of call options. Higher (lower) PCR indicates bearish (bullish) sentiment in the market (Brown & Cliff, 2004; Kumari & Mahakud, 2015; Naik & Padhi, 2016).

Trading Volume (VOL): It is a proxy of market liquidity, and higher (lower) trading volume indicates bullish (bearish) sentiment in the market (Baker & Wurgler, 2006; Yang & Gao, 2014; Haritha & Rishad, 2020; Li & Liu, 2021; Sen *et al.*, 2025).

Turnover (TURN): It is a proxy of liquidity that indicates the sentiment in the market (Kumari & Mahakud, 2015; Sen *et al.*, 2025).

3.3 Methodology

To analyse the impact of investor sentiment on the volatility of the Indian Futures Market, a set of non-linear heteroscedasticity models, viz. GARCH (1,1), EGARCH and Diagonal BEKK GARCH Models are used. This study follows the methods of Baker and Wurgler (2006) and Verma and Soydemir (2009) to construct an investor sentiment index using PCA, selecting the first two principal components of sentiment proxies with eigenvalues greater than 1 to capture investor sentiment's impact in the Indian index futures market. To capture the irrational sentiment effect, sentiment shifts (ΔFSI) are included in the mean and variance equation of GARCH models. The ARCH LM test was applied before and after GARCH model estimation to evaluate the ARCH effect.

Models used:

$$\text{Mean Equation: } Y_t = \lambda_0 + \lambda_1 Y_{t-1} + \lambda_2 \Delta FSI + u_t \quad (2)$$

$$\text{GARCH (1, 1): } h_t = \omega_0 + \alpha_1 u_{t-1}^2 + \beta_1 h_{t-1} + \beta_2 \Delta FSI_{t-1} \quad (3)$$

$$\text{EGARCH: } \ln h_t = \omega_0 + \alpha_1 \frac{|u_{t-1}|}{\sqrt{h_{t-1}}} - \sqrt{\frac{2}{\pi}} + \beta_1 \ln(h_{t-1}) + \beta_2 \Delta FSI_{t-1} + \delta \frac{u_{t-1}}{\sqrt{h_{t-1}}} \quad (4)$$

$$\text{DIAGONAL BEKK GARCH: } H_t = C'C + A'e'_{t-1}e'_{t-1}A + B'H_{t-1}B \quad (5)$$

A bivariate matrix is represented as:

$$A = \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix}, B = \begin{pmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{pmatrix}, C = \begin{pmatrix} c_{11} & 0 \\ c_{21} & c_{22} \end{pmatrix}$$

GARCH (1,1) Model was developed by Bollerslev (1986). Y_t represents futures returns, ΔSI_{t-1} represents lagged sentiment changes (SI), h_t represents conditional variance, u_{t-1}^2 lagged squared residuals. The EGARCH model, developed by Nelson (1991), captures asymmetric effects between positive and negative returns. α_1 represents the magnitude effect, and β_1 represents the persistence of conditional volatility. δ is the asymmetric coefficient.

The Diagonal BEKK GARCH Model developed by Robert F. Engle and Kenneth F. Kroner (Engle & Kroner, 1995) analyses the spillover effect between the Sentiment Index and futures return. This model effectively captures the time-varying volatility and spillover effect between futures returns and investor sentiment variables within a multivariate framework. Unlike the univariate GARCH models, it accounts for interdependencies across variables. This model paves the way for the past sentiment and volatility shocks to affect current volatility, explaining a sentiment and volatility spillover effect. The diagonal BEKK GARCH model has lower parameter complexity than the BEKK model and captures own-market and

cross-market spillover effects; hence, it is suitable for analysing the dynamic relationship between futures volatility and investor sentiment.

A and B are the $n \times n$ matrices of parameters, and C is the upper triangular matrix of parameters (Engle & Kroner, 1995).

3.4 Investor sentiment index development

The investor sentiment effect on index futures market volatility is investigated by developing an index using seven sentiment proxies. According to Brown and Cliff (2004), market-related sentiment proxies can help measure investor sentiment. Baker and Wurgler (2006) first proposed an approach to constructing an investor sentiment index based on the first principal component of sentiment proxies. Verma and Soydemir (2009) expanded this approach to capture the sentiment effect on returns. Most researchers investigating investor sentiment and financial market volatility have used the sentiment index creation using PCA method proposed by Baker and Wurgler (2006) and Verma and Soydemir (2009) for their analysis (Baker *et al.*, 2012; Kumari & Mahakud, 2015, 2016; Naik & Padhi, 2016; Haritha & Rishad, 2020; Chen *et al.*, 2021; Li & Liu, 2021; Andleeb & Hassan, 2025). This study also follows the methods of Baker and Wurgler (2006) and Verma and Soydemir (2009) for index construction using PCA by taking the first two principal components of sentiment proxies, viz., OI, VIX, MMI, RSI, PCR, Turnover and Trade Volume.

Correlation between all sentiment proxies was performed before PCA, revealing a strong correlation between them (Table 1). The KMO test result in Table 2 shows a value greater than 0.5, indicating that the data set is suitable for doing PCA. Bartlett's Sphericity Test gives a p -value less than 0.05, confirming that variables are independent. These test results indicate that performing PCA using this data set is effective. The Exchange Rate is used as the macro-economic variable for regressing all proxies to remove business cycle variations using the equation:

$$Y_t = \alpha_0 + \beta_1 EXRT + \varepsilon_0 \quad (6)$$

Table 1. Correlation table

	OI	VIX	PCR	MMI	RSI	TURN	VOL
OI	1	-0.2666	0.2723	0.03062	0.0819	-0.4144	-0.0878
VIX	-0.2666	1	-0.3149	-0.12742	-0.2999	0.5185	0.6767
PCR	0.2723	-0.3149	1	0.26518	0.4478	-0.4151	-0.3178
MMI	0.0306	-0.1274	0.26518	1	0.7186	-0.3114	-0.2668
RSI	0.0819	-0.2999	0.44782	0.71861	1	-0.4246	-0.4426
TURN	-0.4144	0.5185	-0.41511	-0.31138	-0.4246	1	0.7970
VOL	-0.0878	0.6767	-0.31775	-0.26680	-0.4426	0.7970	1

Note(s): Correlation between all proxies indicates that they are correlated

Source(s): Authors' calculation

Table 2. KMO and Bartlett's test results

KMO test		Bartlett test of sphericity	
Statistic	Chi-square	df	p value
0.635	33109.586	91	0.000

Note(s): KMO and Bartlett's test results show that the dataset is suitable for PCA analysis

Source(s): Authors' calculation

whereas Y_t is the sentiment proxy, β_1 is the parameter to be estimated, EXRT is the Exchange Rate and ε_0 is the error term (Baker & Wurgler, 2006; Verma & Soydemir, 2009). Residual values obtained from this equation are termed irrational components used as the orthogonalised sentiment proxies for constructing the final sentiment index (FSI).

Following Baker and Wurgler (2006), the first four principal components of seven variables and the lagged values of the variables are used for the First Stage Index (FISI), and whichever variables' lead value or lag value has the highest correlation with the FISI were taken for FSI construction. The first and second principal component of the FSI, having 68.9% of sample variance (Table 3), gives the equation:

$$SI_t = 0.6357VOL_{t-1} + 0.2522TURN_{t-1} - 0.1312OI_t + 0.3765VIX_t + 0.2327RSI_{t-1} + 0.0110PCR_t + 0.3491MMI_t \tag{7}$$

4. Analysis and interpretation

This study aims to evaluate the impact of investor sentiment on the volatility of the Indian Index Futures Market using the Sentiment Index (FSI) and Nifty 50 futures index returns.

4.1 Descriptive statistics

Table 4 indicates descriptive statistics of all sentiment proxies, returns and indices. Kurtosis values for all proxies, Returns and indices indicate that the distributions do not follow a Gaussian distribution; returns and sentiment indices are leptokurtic, with values greater than 3. The Jarque-Bera (J-B) test determines whether the data are normally distributed. The null hypothesis is rejected for all indices at a 5% significance level, proving that these data are not normally distributed.

4.2 Testing of unit roots and correlation of indices

The unit root test is conducted to check whether the data are stationary. The Augmented Dickey-Fuller Test (ADF) is used to check the unit root of data. The null hypothesis indicates the presence of unit roots in returns. The ADF test results in Table 5 show that the futures Return, FISI and FSI show a p-value of less than 5%, confirming that the futures return, FSI and SI are stationary.

As shown in Table 5, the correlation between FSI and FISI is 0.949, indicating that the risk of losing information from FSI by dropping the seven proxies with the lowest correlation with FISI is much lower.

4.3 Investor sentiment impact on Indian index futures market volatility

This study employs two univariate non-linear conditional volatility models, viz. GARCH(1,1) and EGARCH to measure the impact of investor sentiment on the volatility of the Indian index futures market. We incorporated sentiment shifts in both mean and variance equations in the GARCH

Table 3. Total variance explained by PCA

Component	Eigenvalue	Difference	Proportion	Cumulative
Comp1	2.483	0.631	0.395	0.395
Comp2	1.853		0.294	0.689

Note(s): Table 3 shows the variance explained by PCA, in which the first two principal components (68.9%), having an eigenvalue greater than one, are selected for FSI development

Source(s): Authors' calculation

Table 4. Descriptive statistics

Variable	Mean	Max	Min	SD	Skewness	Kurtosis	J-B test (<i>p</i> -value)
VOL	10,169,294	51,619,575	1,428,150	4,412,160	2.140702	13.16977	8461.944 (0.0000)
TURN	1,311,734	4,929,232	166084.3	519219.4	1.16499	6.087276	1039.73 (0.0000)
OI	14,345,509	30,746,250	1,768,725	6,043,020	0.502974	2.342201	100.402 (0.0000)
VIX	17.47466	83.6075	10.135	7.324917	3.816127	25.01494	37732.17 (0.0000)
RSI	56.02081	86.2232	12.56072	12.77319	-0.25887	2.662307	26.5548 (0.0000)
PCR	0.967192	1.653301	0.564852	0.12214	0.822555	5.195431	523.0781 (0.0000)
MMI	51.06938	89.48647	10.93807	17.98205	-0.13928	2.097978	61.9414 (0.0000)
EXRT	72.93143	83.2553	63.3482	5.61881	0.156439	2.201635	51.102 (0.0000)
FSI	0.057999	12.71775	-2.55152	1.568967	1.921597	11.0595	5540.931 (0.0000)
FISI	0.064509	15.1975	-2.84462	2.047435	2.301309	12.76576	8100.516 (0.0000)
Returns	0.000526	0.093385	-0.14026	0.011212	-1.48378	27.34471	41802.27 (0.0000)

Note(s): FISI-First Stage Index. FSI- Sentiment Index or Final Sentiment Index

Source(s): Secondary data

Table 5. ADF test results and correlation matrix

ADF test			Correlation matrix			
	<i>t</i> -statistic	<i>p</i> -value		FISI	FSI	Return
<i>FISI</i>	-4.00525	0.0014	<i>FISI</i>	1	0.949018	-0.07473
<i>FSI</i>	-5.84988	0.0000	<i>FSI</i>	0.949018	1	-0.05704
<i>Return</i>	-14.4864	0.0000	<i>Return</i>	-0.07473	-0.05704	1

Note(s): ADF test results show that Final Sentiment Index, First Stage Index and futures index return are stationary

Source(s): Authors' calculation

models to measure the investor sentiment effect. Nifty 50 futures returns are taken as the representative of the Futures Market. The kurtosis values of FSI and returns show that distributions are leptokurtic, and the JB test results confirm that the data series is not normal. Hence, non-linear models can be used to model volatility. ARCH LM test is used to check the presence of the ARCH effect in the return series, which gives a *p*-value of 0.00, confirming the presence of the ARCH effect [1] in the return series. So, it is possible to apply non-linear models to return series.

Table 6 with GARCH (1,1) and EGARCH models incorporating sentiment shifts (Δ FSI). In GARCH models, α indicates the ARCH term, β indicates the GARCH term and the sum of these values is close to 1, indicating a higher degree of volatility persistence in the market. The GARCH (1,1) and EGARCH models capture the symmetric and asymmetric effects on volatility, respectively.

The results of all models, including sentiment shifts, give significant positive α and β values, indicating that the past residual and past conditional variance terms can explain volatility persistence. The sum of the values of α and β of the GARCH (1,1) model gives a

Table 6. GARCH results

Conditional volatility model estimates with sentiment (ΔFSI)		
Parameters	GARCH 1,1	EGARCH
λ_0	0.000868***	0.000734***
λ_2	-0.001165***	-0.0011***
w_0	0.000002***	-0.253865***
α_1	0.071807***	0.116661***
β_1	0.906601***	0.141279***
β_2	0.000011***	0.141279***
δ		-0.080742***
Log Likelihood	5788.346	5811.681
AIC	-6.699126	-6.725007
SIC	-6.677009	-6.699729
HQ	-6.690944	-6.715656
ARCHLM	2.74256 (0.0979)	3.141617 (0.0765)
Ljung Box Test	2.7472 (0.097)	3.1462 (0.076)

Note(s): *, ** and *** denote significance at 10, 5 and 1%, respectively. α_1 is the ARCH term, β_1 is the GARCH term, δ is the asymmetric coefficient, λ_2 is the sentiment term in the mean equation and β_2 is the sentiment term in the variance equation. *p*-values of ARCHLM and Ljung Box tests are given in parentheses

Source(s): Authors' calculation

value close to 1, indicating that volatility is persistent in the futures market. EGARCH results give a significant negative coefficient δ value, indicating that asymmetric volatility or leverage effect is present in the Indian futures market, indicating that investors are prone to negative news rather than positive news, and $\delta < 0$ indicates that negative shocks have a higher effect on volatility than positive shocks. A significant positive α value indicates that yesterday's volatility significantly affects today's volatility and β value indicates that volatility is persistent in the Indian Index Futures market.

To assess the investor sentiment impact on futures market volatility, the Sentiment shift (ΔFSI) is included in both the mean (λ_2) and variance equation (β_2) of both models. The significant negative coefficient values of SI shifts (λ_2) in both GARCH (1,1) and EGARCH models indicate that investor sentiment changes have a negative effect on Nifty 50 futures returns, which means that investors are bearish or pessimistic about the returns in the futures market when there is huge volatility in the market. The β_2 coefficient value, indicating the lagged sentiment shifts in the conditional variance equation, shows a significant positive value, which means that an increase in sentiment or bullish sentiment creates higher volatility in the Indian index futures market. This means that an increase in sentiment shift creates aggressive trading, which creates huge volatility in the futures market. These findings support the theoretical explanation that noise traders make trading decisions based on non-fundamental information, resulting in higher volatility and lower returns.

4.4 Robustness check

ARCH-LM and Ljung-Box tests are diagnostic tests that assess the robustness of GARCH models (Table 6). All GARCH models incorporating sentiment have an insignificant *p*-value for the ARCH LM test, proving the absence of an ARCH effect in the residuals. The Ljung-Box test shows a *p*-value greater than 0.05, indicating no serial correlation in the residuals. Therefore, all these models are suitable for measuring volatility in the futures market. Akaike Information Criteria (AIC), Schwarz Information Criteria (SIC) and Hannan–Quinn Criteria (HQ) are used to identify the superior model, and the model with the lowest AIC, SIC and HQ values is taken as the most suitable model (Chen et al., 2021). The results reveal that the EGARCH model is superior, as it has the highest log-likelihood value and the lowest AIC, SIC and HQ values.

4.5 Structural break analysis

This analysis is carried out to determine whether there is a structural break in the data series. The Quandt–Andrews unknown breakpoint test result (Table 7) and the Chow test result (Table 8) shows a significant p -value, indicating a structural break in the data series on 24/03/2020. This date aligns with the nationwide lockdown due to the COVID-19 pandemic, which triggered high uncertainty and panic across financial markets. This period shows a sudden change in volatility, returns and the risk-return relationship in the Indian index futures market. Specifically, this period is characterised by a sharp increase in volatility, intensive speculative trading and altered investor sentiment.

However, the GARCH (1,1) and EGARCH models show insignificant dummy variables, as reported in Table 9, indicating that the structural break identified during the COVID-19 pandemic can be interpreted as a temporary disruption followed by mean reversion in the futures market. The abrupt shift in March 2020 reflected a sharp deviation in prices and volatility from their long-run equilibrium due to extreme uncertainty, panic-driven trading and a shift in sentiment; however, as markets gradually absorbed information and policy interventions, prices began to revert toward their fundamental or long-term average levels (Tripathi & Dixit, 2023; de Oliveira, Mandal, & Power, 2024; Yang, 2025).

Table 7. Quandt–Andrews unknown breakpoint test result

Quandt–Andrews unknown breakpoint test		
Null Hypothesis: No breakpoints within 15% trimmed data		
Varying regressors: All equation variables		
Equation Sample: 1/03/2017 12/29/2023		
Test Sample: 1/18/2018 12/12/2022		
Number of breaks compared: 1,209		
Statistic	Value	Prob.
Maximum LR F-statistic (3/24/2020)	28.26939	0.0000
Maximum Wald F-statistic (3/24/2020)	56.53879	0.0000
Exp LR F-statistic	7.083837	0.0000
Exp Wald F-statistic	21.17356	0.0000
Ave LR F-statistic	0.746052	0.5621
Ave Wald F-statistic	1.492104	0.5621
Note(s): Probabilities calculated using Hansen's (1997) method		
Source(s): Authors' calculation		

Table 8. Chow test result

Chow Breakpoint Test: 3/24/2020			
Null Hypothesis: No breaks at specified breakpoints			
Varying regressors: All equation variables			
Equation Sample: 1/03/2017 12/29/2023			
Test statistic	Value	Probability	
F -statistic	28.26939	Prob. $F(2,1724)$	0.0000
Log likelihood ratio	55.76055	Prob. Chi-Square(2)	0.0000
Wald statistic	56.53879	Prob. Chi-Square(2)	0.0000
Source(s): Authors' calculation			

Table 9. GARCH results (including structural break)

Conditional volatility model estimates with sentiment (ΔFSI)		
Parameters	GARCH 1,1	EGARCH
λ_0	0.000751***	0.000364***
λ_2	-0.001305***	-0.001322***
Dummy	0.000118 (0.7373)	0.000437 (0.1282)***
w_0	0.000002***	-0.230643***
α_1	0.085023***	0.115483***
β_1	0.899004***	0.985151***
β_2	0.000011***	0.167277***
δ		-0.071718***
Log Likelihood	5758.03	5791.016
AIC	-6.663998	-6.701061
SIC	-6.641881	-6.675784
HQ	-6.655816	-6.691711
ARCHLM	1.657006 (0.1982)	3.710330 (0.0542)
Ljung Box Test	1.6608 (0.197)	3.7144 (0.054)
Note(s): *, ** and *** denote significance at 10, 5 and 1%, respectively. α_1 is the ARCH term, β_1 is the GARCH term, δ is the asymmetric coefficient, λ_2 is the sentiment term in the mean equation and β_2 is the sentiment term in the variance equation. <i>p</i> -values of ARCHLM and Ljung Box tests are given in parentheses. Dummy is the coefficient used to represent a structural break in the data series		
Source(s): Authors' calculation		

Literature confirmed that after the first quarter of 2020, the responsiveness of stock markets to pandemic-related developments decreased significantly, indicating that investors had adapted to the pandemic and began treating rising case numbers as less relevant, leading to normal trading behaviour in which such information has a reduced impact on their sentiments and trading decisions (Yang, 2025). This led to mean reversion and the market gradually adjusted, moving back to the fundamental equilibrium.

4.6 Sentiment – volatility spillover effect analysis

The Diagonal BEKK GARCH model is used to investigate the spillover effect between the Investor Sentiment and the Indian Futures market returns volatility. The mean equation talks about the return spillover between investor sentiment (ΔFSI) and futures return, and the variance equation explains the volatility spillover effect between these series.

4.6.1 Return spillover results. The mean equation result in Table 10 gives a mean return spillover effect between sentiment index and index futures. The significant coefficient values of C (2) indicate that returns depend on its previous lags, and C (3) shows that the futures return depends on the previous day's sentiment changes. The coefficient values of C (5) and C (6), having a *p*-value of 0.00, indicate that yesterday's sentiment shifts and returns significantly affect today's investor sentiment changes. This result indicates a bidirectional return spillover effect between the sentiment and futures indices. It reveals that the rapid flow of information on sentiment changes of investors and past returns information directly affects Indian Futures returns and sentiment changes in future.

4.6.2 Volatility spillover effect. The conditional variance and covariance equation explaining the spillover effect between sentiment shift and volatility is given further in the text:

$$h_{11,t} = 1.74E^{-06} + 0.060447u_{1,t-1}^2 + 0.921379h_{11,t-1} \tag{8}$$

$$h_{12,t} = 2.30E^{-07} + 0.098453u_{1,t-1}u_{2,t-1} + 0.751940h_{12,t-1} \tag{9}$$

Table 10. Diagonal BEKK GARCH results

Diagonal BEKK GARCH model				
Mean equation coefficients				
	Coefficient	Std. error	z-statistic	Prob.
C(1)	0.000851	0.000173	4.915147	0.0000
C(2)	0.072069	0.023774	3.031401	0.0024
C(3)	0.000616	0.000225	2.741222	0.0061
C(4)	−0.00209	0.015414	−0.135274	0.8924
C(5)	−0.31506	0.022773	−13.83477	0.0000
C(6)	−23.6518	1.443971	−16.37965	0.0000
Covariance specification				
Transformed variance coefficients				
	Coefficient	Std. error	z-statistic	Prob.
M(1,1)	0.000002	0.000001	3.272477	0.0011
M(2,2)	0.132237	0.025027	5.283827	0.0000
A1(1,1)	0.245855	0.02152	11.42427	0.0000
A1(2,2)	0.400452	0.039133	10.23313	0.0000
B1(1,1)	0.959885	0.00686	139.9205	0.0000
B1(2,2)	0.783365	0.037586	20.8421	0.0000

Note(s): A1 indicates the ARCH term, and B1 indicates the GARCH term. A significant *p*-value indicates a significant return or volatility and sentiment spillover effect in the futures market

Source(s): Authors' calculation

$$h_{22,t} = 0.132237 + 0.160362u_{2,t-1}^2 + 0.613661h_{22,t-1} \quad (10)$$

The variance equation result in [Table 10](#) gives a significant ARCH term for both returns (0.060447) and sentiment shifts (0.160362) reveals an own volatility spillover effect and the GARCH coefficient values of own volatility persistence of returns (0.921379) and sentiment index (0.613661), indicating that volatility persistence in the futures market and sentiment index is based on its own past error terms and conditional variance or volatility.

The cross-volatility spillover effect between sentiment shifts and the returns indicates that the rapid flow of information about sentiment changes today has an influence on future volatility, and past futures return information has an influence on investor sentiment changes in the future. The own spillover effect of return is higher than the cross-volatility spillover effect between sentiment shift and return, and the own volatility spillover effect of sentiment index shifts. This result indicates a bidirectional cross-volatility spillover effect between the investor sentiment changes and volatility in the Indian Index Futures Market.

5. Discussion

The empirical findings indicate that investor sentiment plays a significant role in influencing both returns and volatility in the futures market. These findings are consistent with recent empirical evidence from India, where investor sentiment has been shown to significantly contribute to excess volatility and return dynamics in the stock market when modelled using GARCH models ([Kumari & Mahakud, 2015](#); [Haritha & Rishad, 2020](#)).

The GARCH model results reveal a statistically significant negative relationship between investor sentiment and futures returns, suggesting that investors become pessimistic about futures returns when market volatility is high. Furthermore, the analysis identifies a significant positive relationship between changes in sentiment and market volatility, implying that shifts

toward optimistic or bullish sentiment can intensify volatility in the Indian futures market. This behaviour is also accompanied by a pronounced leverage effect, where negative shocks have a stronger impact on volatility than positive shocks. The positive relationship between changes in investor sentiment and market volatility suggests that increases in optimistic or bullish sentiment encourage aggressive trading behaviour, thereby intensifying volatility in the futures market. This implies that during periods of heightened optimism, investors tend to engage in speculative, sentiment-driven trading, which contributes to excessive price fluctuations and market instability.

Such findings are consistent with the behavioural finance literature, which suggests that noise traders rely on emotions, market perceptions and non-fundamental information rather than intrinsic asset values, thereby causing overreactions to optimistic sentiment that result in overvaluation, price distortions, increased volatility and lower risk-adjusted returns in financial markets (Ryu *et al.*, 2023; Xiang, Ma, & Liu, 2024; Maretta & Redwood, 2025). Since optimistic or pessimistic sentiment can amplify volatility and lead to excessive price fluctuations, investors should avoid making decisions solely based on emotions, rumours or herd behaviour. Instead, trading decisions should be supported by fundamental analysis, technical indicators and proper market information. Effective risk management practices, including stop-loss strategies, portfolio diversification and prudent leverage management, are essential to minimise potential losses arising from sudden market fluctuations.

The Diagonal BEKK GARCH model confirms the existence of a bidirectional spillover effect between changes in investor sentiment and returns, as well as between sentiment changes and volatility in the Indian Index Futures Market. The findings indicate that changes in investor sentiment from the previous day significantly influence current futures returns and market volatility, while past returns and volatility also affect subsequent investor sentiment. This reciprocal relationship exists because investor sentiment and market movements continuously interact, with market performance influencing investor emotions and behaviour, while sentiment-driven trading activities simultaneously affect market dynamics. This finding is consistent with the results of Bai, Jung, and Li (2024), which confirms a spillover effect between stock market volatility and investor sentiment.

Investor sentiment shifts affect futures returns and volatility because optimistic or pessimistic expectations influence trading decisions, risk-taking behaviour and speculative activities. At the same time, market returns and volatility also shape future investor sentiment, as investors react emotionally to past gains, losses and market uncertainty. Positive returns generally increase investor confidence and optimism, whereas negative returns and heightened volatility generate fear and pessimism, thereby creating a feedback mechanism between sentiment and market dynamics. This reciprocal relationship is further strengthened in futures markets due to leverage, rapid information transmission and speculative trading behaviour. News or information related to investor sentiment shifts can significantly affect market returns and volatility, while information concerning fluctuations in returns and volatility can also influence investor sentiment and future market expectations (Yang & Gao, 2014; Chen *et al.*, 2021).

Understanding these spillover dynamics enables investors to make more informed, disciplined and risk-adjusted investment decisions in the highly volatile futures market by helping them anticipate sentiment-driven market fluctuations, evaluate potential risks and return patterns more effectively, improve market timing and forecasting ability and adopt appropriate risk management strategies such as hedging, diversification and stop-loss mechanisms to minimize potential losses arising from sudden changes in market sentiment and volatility.

6. Conclusion

This study evaluates the impact of investor sentiment on the Indian index futures market. A sentiment index was constructed using the first and second principal components of seven

sentiment proxies and incorporated into the mean and variance equations of the GARCH (1,1) and EGARCH models to capture the sentiment impact on futures returns and volatility.

The analysis using both models incorporating sentiment shows that sentiment negatively affects returns and positively affects volatility. EGARCH reveals a leverage effect, indicating that negative shocks affect volatility more than positive shocks in the futures market. The results show that the EGARCH model is superior, as it has the highest log-likelihood value and the lowest AIC, SIC and HQ.

The diagonal BEKK GARCH model results show a significant bidirectional volatility and sentiment spillover effect in the futures market. This shows that the rapid flow of information about sentiment changes the previous day significantly affects the returns and volatility of the futures market today and vice versa.

This study contributes to the existing behavioural finance literature by providing empirical evidence of significant sentiment and return–volatility spillover effects in the Indian index futures market, an area that has received limited research attention. The findings demonstrate that investor sentiment is a key determinant of futures market volatility, highlighting the importance of incorporating behavioural and emotional factors into volatility forecasting and risk assessment. These insights encourage market participants to adopt more disciplined and informed trading strategies rather than relying on emotions, rumours, herd behaviour or short-term market excitement. These findings also provide a useful foundation for future research on sentiment-driven behaviour and volatility transmission in emerging derivatives markets.

7. Implications and future research scope

The findings have important implications for investors, portfolio managers, financial analysts, policymakers and market regulators by demonstrating that investor sentiment is a key determinant of returns, volatility and overall market dynamics in the Indian index futures market. By highlighting the significant role of behavioural factors in shaping market movements, the study provides valuable insights for improving investment decisions, risk management and market surveillance. The negative relationship between investor sentiment and futures returns suggests that periods of heightened uncertainty and pessimism are associated with lower returns, while the positive relationship between sentiment changes and volatility indicates that shifts in investor expectations can trigger substantial fluctuations in market risk. Therefore, investor sentiment should not be viewed merely as a supplementary indicator but as an early warning signal that enables investors to anticipate periods of heightened uncertainty and adjust portfolio allocations, hedge ratios and leverage accordingly. Integrating sentiment indicators, such as the India VIX, Put–Call Ratio (PCR), RSI, trading volume, turnover and market mood indicators, with traditional technical and fundamental analysis can improve market timing, behavioural trend analysis, volatility forecasting and risk-adjusted investment decisions.

The asymmetric volatility results obtained from the EGARCH model provide a particularly important practical implication. This finding suggests that investors should respond differently to favourable and unfavourable information. During periods of adverse news or pessimistic sentiment, investors/portfolio managers may need to adopt more conservative trading strategies by reducing leveraged positions, increasing hedging activity, maintaining higher liquidity reserves and revising risk limits, as downside risks rise faster than upside opportunities. Conversely, during periods of positive news or optimistic investor sentiment, investors and portfolio managers should avoid excessive risk-taking and overconfidence, as bullish sentiment may encourage speculative trading, temporary overpricing and the formation of market bubbles. Instead, they should maintain disciplined portfolio allocation, periodically rebalance portfolios to prevent excessive exposure to overvalued assets, use profit-taking strategies where appropriate, adhere to predetermined position limits and continuously monitor sentiment indicators for signs of market exuberance. Recognising the asymmetric effects of investor sentiment on volatility can help investors and portfolio

managers make more resilient, disciplined and risk-sensitive trading decisions across different market conditions.

The significant bidirectional spillover between investor sentiment and futures market returns and volatility further demonstrates that market sentiment and market performance continuously reinforce each other. Since sentiment influences future market movements and market outcomes simultaneously shape subsequent investor expectations, sentiment indicators can serve as forward-looking indicators of potential market instability. This dynamic feedback mechanism enables investors, institutional traders and portfolio managers to anticipate volatility clusters, improve forecasting accuracy and develop proactive trading strategies rather than reacting only after market conditions deteriorate.

The findings also have important implications for policymakers and market regulators that go beyond mere monitoring of market sentiment. The existing literature suggests that sentiment indicators can serve as early warning tools for detecting excessive speculation, abnormal trading activity and emerging financial stress. Consequently, regulators such as SEBI and stock exchanges could incorporate sentiment measures into their real-time market surveillance systems to identify periods when behavioural trading dominates fundamental trading. During episodes of excessive optimism or pessimism, regulators may consider strengthening surveillance of derivative positions, reviewing margin requirements, issuing investor advisories to discourage speculative trading, enhancing disclosure requirements for large market participants and conducting targeted investigations into abnormal trading patterns. Such measures can help reduce the formation of speculative bubbles, improve market discipline and preserve the integrity and stability of the derivatives market.

Understanding investor behaviour in the futures market is particularly important because the Indian index futures market performs critical economic functions, including price discovery, risk transfer and liquidity provision. Persistent sentiment-driven distortions may reduce the efficiency of these functions by causing futures prices to deviate from their fundamental values. Since index futures play a leading role in incorporating new information into market prices, excessive sentiment-driven volatility may spill over into the underlying spot market through arbitrage and information transmission. Such spillovers can influence equity prices, institutional portfolio valuations, corporate financing conditions and overall investor confidence, thereby extending the consequences of behavioural trading beyond the derivatives market to the broader financial system.

The study, therefore, contributes to behavioural finance by demonstrating that investor sentiment has implications that extend beyond individual investment decisions. Understanding sentiment dynamics enables regulators to strengthen market resilience, assists exchanges in improving surveillance mechanisms and helps institutional investors develop more effective volatility forecasting and risk management models. Ultimately, incorporating behavioural indicators into financial decision-making and regulatory frameworks can contribute to more efficient price discovery, improved market stability and a more resilient Indian financial market.

The findings support the argument that financial markets are not always fully efficient and that psychological and behavioural factors can significantly influence market dynamics. Thus, the study provides a foundation for future research on sentiment-driven behaviour, volatility spillovers and behavioural biases in emerging financial markets. Researchers may examine the relationship between investor sentiment and other segments of the derivatives market, including commodity and currency futures markets. Comparative studies between emerging and developed markets may also provide broader insights into sentiment-driven market behaviour. Researchers can incorporate alternative sentiment measures, such as social media sentiment, news-based sentiment indices and textual analysis techniques, to capture behavioural and sentiment aspects more comprehensively. Additionally, advanced econometric and machine learning models can be used to examine nonlinear relationships, regime shifts and sentiment spillovers.

Note

1. ARCH LM test Results are given on request.

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