Investor Sentiment Dynamics and Stock Returns: Evidence from Indian Market

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Abstract: *This research explores the connection between market-wide investor sentiment and stock market return within the framework of the Indian stock market. The study investigates how investor sentiment affects stock market returns, specifically examining the Nifty50 indices in the Indian stock market between April 2013 and March 2023. By employing PCA, we developed a sentiment index (SENT) for investors using five proxy market variables for sentiment. We used the VAR model, VAR Granger causality tests, impulse response, and Variance decomposition analysis to investigate how the sentiment index relates to market returns. The findings indicate that the Sentiment Index Granger-causes stock returns, highlighting its predictive value. Short-term shocks to the Sentiment Index significantly impact stock returns, while the effect of stock returns on sentiment is minimal and only temporary. Furthermore, the results show that stock returns are primarily influenced by their past values, but over time, the Sentiment Index increasingly influences variations in stock returns. This supports a moderate positive relationship between investor sentiment and market behavior. The findings contribute to a deeper understanding of behavioral finance in emerging markets and offer valuable insights for investors, policymakers, and finance professionals.*

Keywords: *Investor sentiment index, Stock market return, Principal component analysis, VAR Model*

Introduction

India's stock market has shown significant progress and expansion in recent decades, becoming the world's fourth largest market in terms of market capitalization by 2024 (Fortune India, 2024). The growth has attracted investors from both within the country and overseas to India's stock market, known for its changing prices and returns. The stock market in India, a rising market with potential risks commonly found in developing economies, is responsive to different triggers (Idrees, S. M., Alam, M. A., & Agarwal, P. (2019). Traditional financial theories assume that investors are rational and spread out their investments to increase their returns. Nevertheless, behavioral finance disagrees with this idea, suggesting that investors frequently make irrational choices influenced by feelings like hope, doubt, anxiety, and desire (PH, H., & Rishad,

A. (2020). These feelings greatly impact market trends, causing prices to quickly rise in bullish times and sharply fall in bearish times. Recent studies with real-world data enhance our knowledge of how investor sentiment affects market behavior. Understanding the impact of investor sentiment on stock market returns is highly important in this context. Ahn, K., & Hambusch, G. (2024), Shen et al. (2023), and Kim et al. (2022) have studied the relationship between sentiment, market volatility, and stock returns. Investor's mood may be affected by economic indicators such as GDP, Inflation, exchange rate, Interest rate etc.

news events, and market trends, shifts between optimism and pessimism, ultimately affecting market conduct. Black (1986) brought up the idea of noise traders, pointing out how sentiment can affect both market liquidity and financial efficiency (Hu, J., Sui, Y., & Ma, F. (2021). Researchers De Long (1990) and Lee et al. (2002) indicates that emotions impact asset pricing models and stock market returns, with their DSSW and LST models paving the way for future investigations. Different models have been used in prior studies to analyze investor sentiment in depth, improving our comprehension of market trends. Investor Feelings can be examined either through surveys, interviews as a direct method or through market data proxies as an indirect method. This research utilizes the second option by employing proxy variables to build a sentiment index and investigate its impact on stock market returns. The proxies like trading volume, turnover, advance-decline ratio, first day of return of IPO, growth rate of new open account, price-earnings ratio etc. are chosen for their connection to sentiment of Investors and are frequently merged through principal component analysis (PCA) to form a composite index (Naik & Padhi, 2016). The empirical analysis uses Correlational matrix, VAR models, Granger causality test, Impulse response functions and Variance decomposition to examine how stock market returns and investor sentiment are dynamically related with each-other. This study provides important information about the secrecy of the Indian stock market and suggests practical applications for investors, policymakers, and academics. The research focuses on the Nifty 50 which is considered a key benchmark of the Indian equity market. With this theoretical and empirical background our study examines the role of Investors sentiment and their impact on the return of the Indian stock market that contributing to our knowledge of market movements.

Review of Literature

The correlation between investor sentiment and asset returns has received a lot of attention from researchers. Ahn, K., & Hambusch, G. (2024) contribute significantly by creating composite sentiment indices for global markets. Their analysis of time series data found that optimism leads to stocks being priced too high, while pessimism leads to stocks being priced too low. This impact is noticeable in stocks with higher sentiment exposure, emphasizing the important role of investor sentiment in asset pricing. Duxbury, D., & Wang, W. (2024) delved deeper into the influence of retail and institutional investor sentiment on the risk-return dynamic. By using sentiment proxies from surveys conducted between 1987 and 2018, they employed models including Random Walk (RW), mixed-data sampling (MIDAS), GARCH, and EGARCH. Their findings indicate that combined investor attitudes negatively influence the mean-variance relationship at both the market and firm levels, underscoring the diverse effects of different investor groups on market dynamics. Wang (2024) expanded on the temporal dimension of sentiment's influence by examining its impact across 30 global markets. The study found that negative sentiment correlates more strongly with lower returns during the day than at night, suggesting that overnight traders make more rational decisions. The influence of sentiment, which varies over time, supports the conclusions of Ahn, K., & Hambusch, G. (2024) and Duxbury, D., & Wang, W. (2024). Idnani, S., Adil, M. H., Mal, H., & Kolte, A. (2023) investigated how economic policy uncertainty (EPU) impacts investor sentiment in India using bounds-testing approach to cointegration and impulse response functions (IRF). Their research offers important understandings on how EPU affects sentiment and market behavior in the Indian context over both the short and long term. The literature consistently highlights the widespread impact of investor sentiment on stock prices PH, H., & Rishad, A. (2020) emphasized the significance of sentiment in predicting stock market returns, as did Baker and Wurgler (2006). Rupande, L., Muguto, H. T., & Muzindutsi, P. F. (2019) expanded this analysis to include the Johannesburg Stock Exchange (JSE), uncovering a striking connection between sentiment and stock return volatility. In addition to stocks, sentiment analysis has been used on different types of assets, like Basta and Molnar's (2018) study on the oil market using wavelet analysis and Idrees, S. M., Alam, M. A., & Agarwal, P. (2019) market volatility prediction model using ARIMA. Incorporating a cognitive perspective, Sivaramakrishnan, S., Srivastava, M., & Rastogi, A. (2017) link financial literacy and well-being to stock market participation, adding a psychological dimension to market dynamics. Tuyon, J., Ahmad, Z., & Matahir, H. (2016) supported this cognitive approach by validating the significant influence of sentiment risk on market returns through cognitive-affective theory. PH, H., & Rishad, A. (2020) and Canbas and Kandir (2009) also reinforced the view that irrational sentiment significantly contributes to excess market returns.

Sentiment and Market Volatility during Crises

Extensive research has been conducted on the influence of investor sentiment in crises, particularly the COVID- 19 pandemic. Bai et al. (2023) examined sentiments in global financial markets using more than 1.28 million news articles, showing that deteriorating pandemic situations had an adverse effect on stock markets. However, a rise in positive feelings enhances stock performance, even in challenging situations, showing its ability to lessen negative effects on the market. Shen et al. (2023) investigated how sentiment affects stock returns and value at risk (VAR) in energy firms amid the pandemic by employing a Chinese investor sentiment index developed with Long Short-Term Memory (LSTM) deep learning. Their findings highlight the importance of emotions in market movements in times of crises. Ung et al. (2024) enhance the forecasting precision of Baker and Wurgler's (2006) investor sentiment index through dynamic adjustments to its elements, offering a better understanding of future stock market returns. This study emphasizes the important role of behavioral finance in comprehending market reactions during crises.

Innovations in Sentiment Analysis and Behavioral Finance

The development of the New Investor Sentiment Index (NISI) by Gong et al. (2020) has given new insights into investor behaviour and market trends through advancements in sentiment analysis. This index showed better predictive accuracy than current indicators during financial crises, providing a stronger tool for predicting market trends in times of pressure. This development adds to the increasing body of literature on sentiment analysis during volatile periods. In the same way, Audrino et al. (2020) found that financial terms searched on Google have predictive value, revealing a new aspect in the connection between investor interest and market fluctuations. Their research highlights the significance of emotional factors in elucidating changes in the market. Furthermore, Hudson et al. (2020) investigated institutional herding behaviour in the UK and found that sentiment has a major impact on collective investor behaviour, especially in times of economic downturns. By integrating blockchain- based contracts and voter profiles with Proof of Authority (POA) and Proof of Vote (POV) consensus techniques, creative ways to lower the risks of bitcoin market hacks may be possible. This approach potentially improves the security and adaptability of decentralized systems, that might boost investor sentiment and reduce market return volatility.

In India, Chakraborty and Subramaniam (2020) emphasized how sentiment affects stock returns and volatility, stating that low sentiment causes fear-based selling, whereas high sentiment results in overvaluation.

Objectives of the Study

1. To investigate the impact of investors' sentiments on return in the Indian stock market.
2. To ascertain the investors' sentiment's role in exacerbating market behavior in time of crisis such as COVID-19 pandemic.
3. To analyse the inter-relationship and causative influence of the Sentiment Index and stock price return using econometric techniques.

Research Method

This section explains the details of variables for conducting the study. The sample period spans from April 2013 to March 2023. Here, we collect two types of data that related to key variables i.e., closing price of nifty fifty indices and another one is regarding proxies of sentiment for constructing Index that develops based on previous studies employing quantitative data to measure investor sentiment and examine the relationship between stock return (Rt) and the sentiment index (SENT). The Nifty 50 closing price is utilized to calculate the return, a key variable in our analysis. The return formula is provided below.

Rt = ln Pt “ ln Pt”1

It represents a logarithm return where Pt is the closing price of the current month t, and Pt”1 is the previous month's price (Hu, J., Sui, Y., & Ma, F. (2021). Based on a comprehensive review of the literature, this study selects following five proxies for measuring investor sentiment.

(i) Trading volume is viewed as an important indicator for sentiment measures. It is the aggregate number of shares exchanged in a certain time-frame, use to evaluate market liquidity and activity. When trading volume increases show more engagement and interest in a specific security, implying high investor enthusiasm and a robust market uptrend. On the other hand, when trading volume decreases that indicate a drop in market participation and engagement from traders and investors. Investor sentiment is measured using NSE monthly trading volume data from the past decade for this research (Rameeza and Arshad, 2024; PH, H., & Rishad, A. 2020; Hu et al., 2021; Naik and Padhi, 2016; Chuang et al., 2010; Zhu, 2012).

(ii) Market turnover is also known as turnover, measures the stock's liquidity for a company. Increased interest and regular trading by investors lead to high share turnover, which is often linked to greater volatility caused by quick fluctuations in price. (Hu et al., 2021; Haritha and Abdul, 2020; Naik and Padhi, 2016; Li, 2014; Dash and Mahakud, 2013; Changsheng and Yongfeng, 2012; Zhu, 2012; Qiang and Shu-e, 2009; Baker and Wurgler, 2006, 2007).

(iii) Advance-decline ratio (ADR): It assess general market sentiment by differentiating between the quantity of advancing and declining securities, aiding traders and investors in comprehending the extent of market activity and patterns. These measures offer understanding of market trends and investor attitudes, essential for developing a sentiment index. The ADR ratio is typically positive as a result of investor sentiment, therefore increasing market activity (Brown, G. W. 2004; PH, H. 2020). ADRs are utilize as a gauge for market sentiment and as an indicator of market performance due to their ability to identify recent market trends. A bullish sentiment is indicated by a high advance-decline ratio. It is a valuable sentiment proxy tool for investors to understand market dynamics and ascertain the right trading or investment decision (Naik and Padhi, 2016; Hu et al., 2021; PH, H., & Rishad, A. (2020); Dash and Mahakud, 2013; Wang et al., 2006; Brown and Cliff, 2004). To calculate ADR following formula use.

$$\text{ADR} = \frac{\textit{Number of Advancing securities}}{\textit{Number of declining securities}}$$

(iv) Growth rate of new issue shares **(NOPEN)** indicates new investor accounts opened in a period, and newly opened accounts in the market indicate the rapidly growing interest of investors. It is calculated by dividing the number of new open Demat accounts by the last month's open accounts. By using this formula, we understand the growth of new open accounts that measure investor sentiment (Hu et al., 2021; Li, 2014; Qiang and Shu-e,2019).

$$\text{NOPEN} = \frac{\Delta OPEN}{TOPEN}$$

(v) First-day return of an IPO (RIPO): According to Baker and Wurgler, the first-day return has and has an impact on investors behavior. Based on much literature, RIPO can be measured by IPO issuing or listing day gain and loss. A positive RIPO could signal optimistic investor sentiment. (Hu et al., 2021; Li, 2014; Baker and Wurgler, 2006, 2007).

(vi) Price – earnings ratio (PER): An investor's initial interest in a company can be reflected through its price-to- earnings (P/E) ratio. Investor sentiment can be measured by the price-to-earnings (P/E) ratio, which reflects market participants' expectations for future earnings and their confidence in a company's performance. Studies have shown that the P/E ratio is influenced by factors such as growth opportunities and dividend payouts, both of which are associated with positive investor outlooks. This impacting investment decisions and stock market trends. Additionally, high P/E ratios often indicate that investors are optimistic and willing to pay a premium for earnings potential, signaling stronger sentiment in the market (Jitmaneeroj, B. (2017); Dutta, K. D., Saha, M., & Das, D. C. (2018).

These indicators, influenced by factors such as liquidity, market structure, and the presence of institutional investors, reflect investor sentiment and are employed in constructing a composite sentiment index through principal component analysis (PCA).

Construction of Investor Sentiment Index

We have taken five emotional sentiment proxy variables, descriptive statistics, and the co-relation coefficients of these variables as shown in Tables 1 and 2. To construct this index, the study requires that the proxy variables be stable; that's why we use a stationary test. There are many statistical tests to determine the stationarity of time series data, but in this study, we use the Augmented Dicky-Fuller (ADF) test in Table 3. A principal component analysis is used here for structuring the composite index.

PC1 = 0.5846LTURN + 0.5809LTV – 0.0069NOPEN -0.1254RIPO + 0.08222 ADR + 0.5460PER

PC2 = 0.0003LTURN + 0.0414LTV + 0.5030NOPEN + 0.6085RIPO + 0.6122ADR + 0.5460PER

PC3 = - 0.03612 LTURN – 0.0001LTV + 0.8473NOPEN – 0.2229RIPO – 0.4759ADR + 0.0699PER

PC4 = 0.0561LTURN + 0.0986LTV – 0.1586NOPEN + 0.7503RIPO – 0.6238ADR +P0.0993PER

PC5 = -0.3749LTURN – 0.4087LTV – 0.0531NOPEN + 0.0052RIPO + 0.0534ADR + 0.8287PER

PC6 = 0.7164LTURN - 0.6957LTV + 0.0328NOPEN + 0.0348RIPO - 0.0145ADR -0.0162PER

Analysis & Results

Model Selection for the VAR Model

The Vector Autoregressive (VAR) model extends univariate autoregressive models, which use lagged values of a single variable to explain its current value, to a multivariate framework. This approach accommodates multiple interdependent time series variables, allowing for a more comprehensive analysis of their dynamic relationships. As noted by Sims (1980), when the number of variables is simultaneous, the distinction between exogenous and endogenous variables becomes irrelevant. In this study, we employ the VAR model to analyse the interaction between investor sentiment (SENT) and the Nifty 50 index of the National Stock Exchange. We select VAR model because both the variable stationary and fulfilled the stability conditions. TABLE 1 presents descriptive statistics for the variables used in the analysis, including the log of trading volume (LTV), the first-day return of the IPO (RIPO), the advance-decline ratio (ADR), the growth in demat account openings (NOPEN), Price – earnings and Market turnover (LTURN), ratio which is calculated as turnover of Nifty 50.

Table 1: Descriptive Statistics

Statistics	LTURN	LTV	NOPEN	RIPO	ADR	PER
Mean	13.31692	15.49226	0.108583	15.73444	94.50833	24.19142
Median	13.32	15.36576	0.115	3.54	93	23.34
Maximum	14.3	16.87436	3.75	157.6	175	40.8
Minimum	12.15	14.72449	-2.8	-63.81	56	16.12
Std. Dev.	0.586258	0.506527	1.17617	34.99034	18.57033	4.714695
Skewness	-0.04046	0.716423	-0.02405	1.873696	0.993822	1.156258
Kurtosis	1.883226	2.5781	3.352384	8.06915	5.437252	4.960565
Jarque-Bera	6.26867	11.15523	0.632436	198.6961	49.45463	45.95774

Source: Author's own calculation

Descriptive statistics provide valuable insights into the distribution and characteristics of each variable. The mean values show the average levels for each metric, with ADR having the highest mean at 94.51, indicating strong average returns. At the same time, NOPEN is close to zero, reflecting slight net open interest. Std. Dev. RIPO shows the highest variability at 34.99, highlighting its volatility, whereas LTURN and LTV have much lower variability, implying stability in trading volume and value. Skewness results indicate that RIPO, ADR, and PER are positively skewed, suggesting a higher frequency of smaller values but with long right tails. In contrast, LTURN and NOPEN are almost symmetric, with skewness close to zero. Kurtosis values for most variables, particularly RIPO (8.07), show leptokurtic distributions, indicating the presence of outliers or extreme values. The Jarque-Bera test confirms that most variables deviate from normality, with significant p-values for LTV, RIPO, ADR, and PER (all $p < 0.05$). Only NOPEN has a p-value above 0.05, suggesting a normal distribution. The skewed and non-normal distributions for RIPO and PER imply potential challenges in analyses that assume normality. The median values are close to the means for LTURN and LTV, indicating relatively symmetric distributions for these variables, while others show more deviation. RIPO shows a high maximum (157.6) and low minimum (-63.81), reflecting large swings in returns, which could influence market stability analysis. ADR and PER also exhibit significant positive skewness and kurtosis, suggesting higher risks in using these variables for prediction models without transformation. The relatively consistent mean and SD. Dev. For LTURN and LTV, they point to stable trading metrics. Overall, skewness and kurtosis in most variables mean that traditional linear models might need adjustments or transformations. The large variability and outlier potential must be managed carefully in econometric modeling, especially in RIPO and ADR. The non-normality highlighted by the Jarque- Bera test results suggests using non-parametric methods or corrections. The sum of squared deviations further emphasizes variability, especially in RIPO and ADR.

Table 2: Correlation Coefficient

Statistics	LTURN	LTV	NOPE	RIPO	ADR	PER
LTURN	1	0.752204	-0.03327	-0.12341	0.089258	0.63374
LTV	0.752204	1	0.002583	-0.08605	0.080497	0.630034
NOPEN	-0.03327	0.002583	1	0.052069	0.036722	0.021788
RIPO	-0.12341	-0.08605	0.052069	1	0.072379	-0.10333
ADR	0.089258	0.080497	0.036722	0.072379	1	0.043528
PER	0.63374	0.630034	0.021788	-0.10333	0.043528	1

Source: Author's own calculation

TABLE 2 the correlation matrix reveals several important relationships among the variables in your study. The Turnover Ratio (LTURN) and the Loan-to-Value ratio (LTV) show a strong positive correlation of 0.752. This indicates that higher turnover is associated with higher loan-to-value ratios. On the other hand, LTURN has a very weak negative correlation of -0.033 with the Number of Open Positions (NOPEN), suggesting that there is little to no relationship between turnover and the number of open positions. Additionally, LTURN and the Rights Issue Price-to-Open ratio (RIPO) display a weak negative correlation of -0.123, indicating a slight inverse relationship. There is also a weak positive correlation of 0.089 between LTURN and American Depository Receipts (ADR), although this is not a strong connection. A moderate positive correlation of 0.633 exists between LTURN and the Price-to-Earnings ratio (PER), suggesting that higher turnover is linked to higher price-to-earnings ratios. Furthermore, LTV and PER have a moderate positive correlation of 0.630, implying that higher loan-to-value ratios are associated with higher market valuations. Overall, the correlations involving NOPEN are weak, indicating that the number of open positions has little relationship with the other variables in your study.

Unit root test for stationarity

To assess the stationarity of time series data, we utilized the Augmented Dickey-Fuller (ADF) test. This test identifies non-stationarity if a time series exhibits changing mean and variance over time, whereas stationarity is indicated by constant properties. The ADF test is favored for its robustness in managing serial correlation and autoregressive processes by incorporating lagged differences of the dependent variable, thus enhancing result. reliability (Dickey & Fuller, 1979). Unlike the Phillips-Perron (PP) or Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests, the ADF test does not impose assumptions on heteroscedasticity or autocorrelation, making it suitable for complex data (Phillips & Perron, 1988; Kwiatkowski et al., 1992). The results, detailed in TABLE 3, confirm variable stationarity, validating the ADF test's application in our analysis.

Table 3: Stationarity Test

Augmented Dicky Fuller Unit Root Test (Trend and Intercept)		
	t-stat	P-value
D(LUTN)	-17.78	0
D(LTV)	-17.44	0
NOPEN	- 17.81	0
RIPO	-8.83	0
ADR	-10.47	0
D(PER)	-7.50	0

Source: Author's own calculatio*n*

The result shows that all variables are stationary at level except trading volume and market turnover, and price earnings ratio which is stationary at first difference. TABLE-3 exabits all the P- values are 0. This expresses good evidence of the null hypothesis where P- the value rejects the null hypothesis when the p-value is less than the 5% significance level for all five variables evident as stationary. So, the condition is fulfilled, we can apply PCA to construct the Investor Sentiment Index. Table - 4 shows the result thereof.

Table 4: The results of PCA

Principal Components Analysis Sample: 2013M04 2023M03						
Included observations: 120						
Computed using: Ordinary correlations Extracting 6 of 6 possible components Eigenvalues: (Sum = 6, Average = 1)						
Variable	PC1	PC2	PC3	PC4	PC5	PC6
LTURN	0.5846	0.000329	-0.03612	0.05613	-0.37491	0.716402
LTV	0.580996	0.041436	-0.00013	0.098566	-0.40865	-0.69571
NOPEN	-0.00693	0.503007	0.847291	-0.15855	-0.05314	0.03276
RIPO	-0.12544	0.608581	-0.22294	0.750303	0.005198	0.034777
ADR	0.082225	0.612213	-0.4756	-0.62384	0.053403	-0.01453
PER	0.546024	0.009566	0.069972	0.099328	0.8287	-0.01615

Source: Author's own calculation

Table 5: Cumulative proportion of proxies

Number	Value	Difference	Proportion	Value	Proportion
1	2.378919	1.270622	0.3965	2.378919	0.3965
2	1.108297	0.139393	0.1847	3.487216	0.5812
3	0.968904	0.074302	0.1615	4.45612	0.7427
4	0.894602	0.491236	0.1491	5.350722	0.8918
5	0.403366	0.157454	0.0672	5.754088	0.959

Source: Author's own calculation

Table 6: Stationarity test of SENT, RT

Augmented Dicky Fuller Unit Root Test (Trend and Intercept)		
Variable	t-stat	P-value
D(SENT)	-5.40	0.0001
RT	-11.32	0.000

Source: Author's own calculation

TABLE 6 shows ADF test statistics is lower than the critical value and the P value (probability value) of both the Sentiment Index (SENT) at first difference and RT at level is very small, so reject the null hypothesis and considered that Sentiment Index and RT (Return) are stationary.

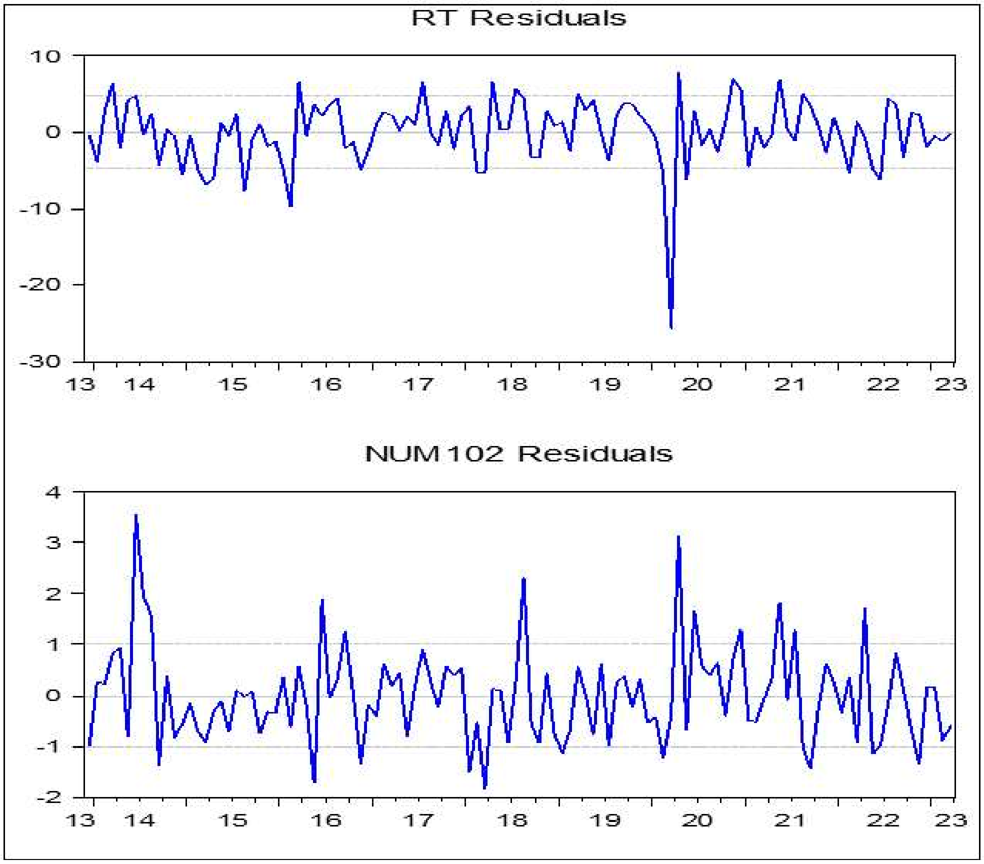

Figure 1: Return and Investor Sentiment Index

Source: Author's own calculation

Figure 1 graphical representations for NUM102 (Sentiment Index) and RT (Return) depict differing degrees of volatility prior to, during, and following COVID-19. Although sentiment affected returns, the relationship was minor and consistent with normal market movements, according to the RT Residuals plot exhibiting comparatively stable fluctuations prior to COVID (2013–2019), over this time period exhibit less extreme variability, suggesting that sentiment changes were stable and that the impact on returns was constant. Sharp, notable fluctuations in the return occurred throughout the COVID-19 pandemic (2020), particularly during market downturns and recoveries. This was indicative of increased uncertainty and a greater response of returns to abrupt changes in sentiment (Altig et al., 2020). Furthermore, during COVID-19, the observed elevated volatility, revealing that sentiment was more Increased volatility was also seen in the during COVID-19, suggesting that investor sentiment was more unstable due to the extraordinary market conditions (Goodell, J. W. (2020). The more noticeable residuals in both plots demonstrate that sentiment was a more significant factor in determining returns during this crisis, with quick shifts in mood causing more intense market reactions. The RT Residuals plot after COVID (2021–2023) indicates a return to more stable but slightly higher fluctuations than before the pandemic, indicating that even if the market recovered its equilibrium, investor mood continued to have a significant impact (Sharma, G. D., Thomas, A., & Paul, J. (2021). Similar to this, show more subdued but enduring mood changes, suggesting that the pandemic's aftereffects continued to influence investor behavior. These findings suggest that during a crisis, mood had a greater impact on market results remained influenced by the pandemic's repercussions.

These results showed that mental states had a greater influence on market returns during times pandemic crisis, whereas the relationship remained stable after the pandemic but remained stronger than it was before COVID. The outcome corresponds with prior research that emphasizes the greater effect of sentiment during periods of significant economic disruption and afterwards gradual adaptation (Smales, L. A. (2021).

Table 7: Correlation matrix

	RT	SENT INDEX
RT	1	0.34
SENT INDEX	0.34	1

Source: Author's own calculation

TABLE 7, the correlation matrix illustrates the relationship between stock returns (RT) and the investor sentiment index (SENT INDEX). The value of 1.000000, which indicates the correlation of RT with itself, is expected, as any variable is perfectly correlated with itself. The correlation value of 0.345931 between RT and the SENT INDEX reflects a moderately positive relationship. This suggests that when investor sentiment increases, stock returns tend to rise, although the correlation is not very strong. A correlation of 0.345931 falls within the "weak to moderate" range, implying that while investor sentiment does influence stock returns, it is not the only factor driving market behavior. This moderate correlation indicates that other variables—such as economic indicators, company performance, or government policies—likely play a more significant role in determining stock returns. Moreover, cultural or structural factors in the Indian stock market may help explain why the relationship between sentiment and returns is not stronger. Although the positive correlation supports the idea that sentiment affects stock returns, it does not serve as the primary determinant. This finding aligns with the understanding that while investor sentiment is important, the strength of its impact on stock returns is influenced by other, more significant market forces.

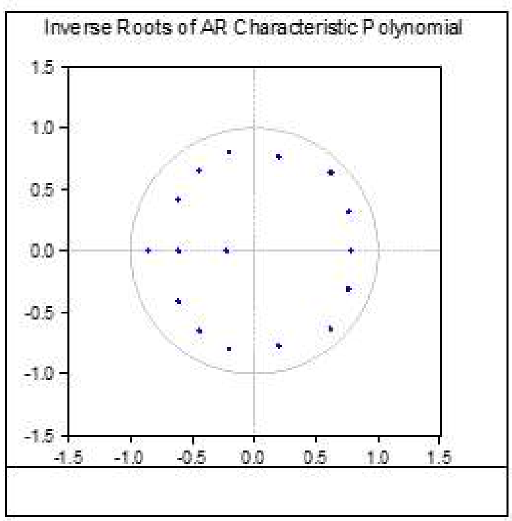

Figure 2: VAR stability Test

Fig.2 represents the Polynomial of a Vector Autoregression (VAR) model, which is used to check the stability of the VAR model, all roots must have a modulus and less than 1 i.e., all the roots must not lie outside the unit circle and it is proved by this model that the VAR model is stable as all the roots lies inside the unit circle and also no serial auto correlation at the selected lag, so it's a good thing for our model. Therefore, it satisfies the stability condition that means the time series data it models will not exhibit explosive behavior, and the model will produce meaningful forecasts and inferences.

Lag length criteria

Selecting the correct lag order is essential to ensure the estimates of a VAR model are accurate and reliable. To identify the optimal lag structure, we have utilized EViews software to perform VAR lag selection criteria. Based on the Akaike Information Criterion (AIC) and Final Prediction Error, the results indicated that a lag order of 2 was appropriate, as shown in the TABLE 8. The selection of lag order based on AIC is widely regarded as the best criterion by many researchers (Lutkepohl, 2005). This indicates that the past three months' data have a significant impact on the current returns.

Table 8: Lag order selection criteria (VAR)

VAR Lag order selection criteria						
VAR Lag Selection Criteria						
Endogenous Variables: RT SENT INDEX Exogenous Variables: C						
Sample: 2013M04 2023M03						
Included Observation: 112						
Lag	Lag L	LR	FPE	AIC	SC	HQ
0	-495.1290	NA	24.57061	8.877304	8.925849*	8.897000*
1	-492.6958	4.736143	25.26837	8.905282	9.050916	8.964370
2	-486.1376	12.53085*	24.14227*	8.859600*	9.102323	8.958080
3	-483.3099	5.301844	24.65813	8.880535	9.220347	9.018407
4	-482.2892	1.877339	26.01509	8.933737	9.370638	9.111001
5	-478.9926	5.945652	26.35910	8.946297	9.480288	9.162954
6	-476.8661	3.759348	27.27855	8.979753	9.610833	9.235802
7	-471.7012	8.946356	26.74733	8.958951	9.687120	9.254392
8	-469.5708	3.614060	27.69663	8.992337	9.817595	9.327170

Note: * indicates the lag order selected by the criteria
LR: Sequential modified LR test statistics (each test at 5% level) FPE: Final prediction error
AIC: Akaike information criterion SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion
***Source**: Author's own calculation*

VAR Granger causality test

TABLE 9 illustrates the short-run causal relationship between market returns (RT) and the investor sentiment index (SENT). This test is used to determine whether one time series can be used to predict another. In this test, the null hypothesis is that Sentiment Index does not Granger-cause stock returns (RT) The p-value of 0.02 is below the conventional alpha level (0.05). This suggests that we are in a position to reject the null hypothesis and say statistically significant Granger-causal effects exist indicating that the Sentiment Index Granger-causes stock returns. It indicates that information from past values of the Sentiment Index is helpful for predicting stock returns. In this case, the null hypothesis is that stock returns (RT) do not Granger-cause the Sentiment Index. From a normal p-value smaller than or equal to 0.05, here we have 0.10 Thus, we cannot reject the null hypothesis and there is no strong evidence of serial correlation among past stock returns with future values of Sentiment Index. The first test (p-value: 0.02), shows that there is one direction Granger-causality, such that: Sentiment Index Granger-causes stock returns (RT). In the other direction (RT does not Granger-cause SENT) there is no significant causal relationship either, with a p-value of 0.10. This result indicates that during the time window studied (2013- 2023), sentiment plays a role in market but changes in the market return not significantly influence investor sentiment.The use of the Granger causality test is justified as it is a widely accepted method for determining causality in time series data (Granger, 1969).

Table 9: VAR Granger Causality / Block Exogeneity Wald Tests

VAR Granger Causality/Block Exogeneity Wald Tests			
Sample: 2013M04 2023M03			
Included observations: 116			
Dependent	Variable: SENTINDEX		
Excluded	Chi-sq	df	Prob.
SENT	13.06	8	0.10
All	13.06	8	0.10
Dependent variable: RT			
Excluded	Chi-sq	df	Prob.
RT	18.10	8	0.02
All	18.10	8	0.02

Source: Author's own calculation

Impulse Response Function (IRF)

The impulse response functions are identified using a Cholesky decomposition with a dependent variable such as market returns (RT) ordered first, i.e., it is contemporaneously affected by other variable shocks like investor sentiment (SENT) by using VAR model. Fig. 3 depicts the IRF, showing how a shock impacts each variable. More precisely, the response of market returns (RT) to a shock in investor sentiment (SENT) is depicted. This figure 2 presents the reaction of Sentiment Index to a stock returns (RT) shock. At first, there is a mild positive effect followed by a negativity in the subsequent periods indicating that stock return shock has both accommodative and constraining effects on sentiment. The impact then dies away to about zero, suggesting that the effect of stock returns on sentiment is limited and short-lived. The Current panel presents the response of stock returns to a shock in the Sentiment Index. Sentiment is measured over longer time periods, and the immediate response is positive: an unanticipated rise in sentiment raises stock returns. But the effect decreases over later periods and is near zero, suggesting that sentiment matters for stock returns in the short run but not the long run. This graph shows how stock returns react to their own shocks. Initial return is high and positive, indicating short-run persistence of returns. The response declines over time but is always greater than zero, indicating that past stock return surprises influence future returns in a persistent manner with persistence decaying over time. Here, the plot shows the impact of a shock to Sentiment Index itself on its future value. The Cholesky decomposition is considered valid because it helps in comprehending the dynamic relationships between variables within a VAR model, as evidenced in the literature (Lütkepohl, 2005).

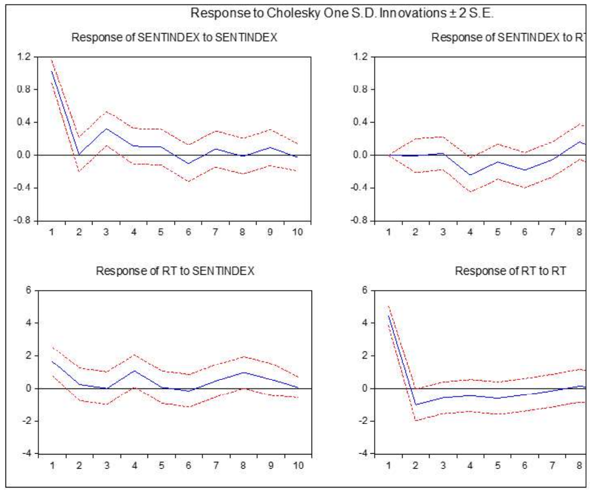

Figure 3: impulse response function

Table 10: Variance Decomposition

Variance Decomposition of SENTINDEX:			
Peri...	S.E.	SENTINDEX	RT
1	1.0225218048...	100	0
2	1.0225938381...	99.997095193...	0.0029048061...
3	1.0739598237...	99.945294954...	0.0547050457...
4	1.1061858253...	95.186681680...	4.8133183199...
5	1.1135961462...	94.743612677...	5.2563873224...
6	1.1323440201...	92.402053849...	7.5979461504...
7	1.1361644513...	92.239271980...	7.7607280197...
8	1.1479596962...	90.364375318...	9.6356246810...
9	1.1519108475...	90.392700806...	9.6072991937...
10	1.1528004977...	90.298003154...	9.7019968456...
Variance Decomposition of RT:			
Peri...	S.E.	SENTINDE	RT
1	4.7626214255...	11.966858798...	88.033141201...
2	4.8703007761...	11.702248789...	88.297751210...
3	4.9030616614...	11.548109896...	88.451890103...
4	5.0390579334...	15.535508038...	84.464491961...
5	5.0746343682...	15.351553042...	84.648446957...
6	5.0907870448...	15.322434189...	84.677565810...
7	5.1148003027...	16.054458644...	83.945541355...
8	5.2104260575...	19.010990849...	80.989009150...
9	5.2397933969...	19.909663179...	80.090336820...
10	5.2406095992...	19.925040816...	80.074959183...
Cholesky Ordering: SENTINDEX RT			

Source: Author's own calculation

Table 10 indicates that the first period, 100% of the variation in SENTINDEX is explained by its shocks, indicating that SENTINDEX is initially driven entirely by its past values. Over time, the proportion explained by RT slightly increases but remains small. By the 10th period, approximately 9.70% of the variation in SENTINDEX is attributed to RT, suggesting that while stock returns influence sentiment, it is limited. In the first period, around 88% of the variation in RT is explained by its shocks, showing strong initial persistence. The contribution of SENTINDEX gradually increases over time, reaching around 19.93% by the 10th period. This indicates that, although stock returns are primarily driven by their past values, the Sentiment Index has a growing and notable impact on the variation in stock returns as the time horizon extends. The variance decomposition analysis reveals that while shocks mostly explain the Sentiment Index's variations, stock returns have a modest and increasing influence over time. Conversely, past values significantly affect stock returns but show a rising influence from the Sentiment Index. This demonstrates that investor sentiment plays an increasingly important role in explaining stock return fluctuations over a longer period. The variance decomposition results show that while stock returns are primarily influenced by their past values, the Sentiment Index increasingly contributes to stock return variation over time, whereas stock returns have a minimal impact on sentiment. The variance decomposition results indicate that stock returns are primarily driven by their past values. However, the Sentiment Index increasingly contributes to variations in stock returns over time, while stock returns have a minimal effect on sentiment.

Conclusion and Implications

This paper offers a detailed examination of the Indian stock market, specifically focusing on the NSE NIFTY50 index, and evaluates how investor sentiment has influenced stock returns from 2013 to 2023. The study examines how investor sentiment impacts market dynamics during the COVID-19 period, using data from NSE, SEBI, and RBI, along with utilizing statistical tools like the Correlation matrix, VAR model, VAR Granger causality, impulse response analysis, and Variance decomposition. The result indicates that investor sentiment has a noticeable short-term effect on stock market returns, but stock returns have a limited feedback effect on sentiment a slight positive relationship between returns and investor sentiment, as given by the VAR model demonstrating the strong impact of historical data on present prices. However, the VAR Granger Causality/Block Exogeneity Wald Tests suggest that during the time window studied, sentiment plays a role in market. From 2013 to 2023, the Sentiment Index Granger-causes stock returns indicating its predictive value for stock returns but stock returns do not Granger-cause the Sentiment Index, suggesting no predictive relationship. while the impulse response analysis reveals shocks to the Sentiment Index significantly impact stock returns in the short term, the influence of stock returns on sentiment is minimal and short-lived. RT and the SENT INDEX reflects the moderately positive relationship between the sentiment index and market returns in India is influenced by the active participation of retail investors and sentiment driven by media coverage. The analysis indicates that investor sentiment had a moderate and consistent impact on market returns before the COVID-19 pandemic. However, during the pandemic, this influence intensified significantly, leading to sharp fluctuations. After the pandemic, sentiment stabilized at slightly higher levels, suggesting that investor sentiment plays a more prominent role during periods of volatility or crisis. These dynamic fuels herd behavior and emotion-based trading, which contribute to market fluctuations (Kumar, A., & Lee, C. M. (2006). Additionally, India's aspirational investment culture, along with a heightened sensitivity to economic and policy developments, strengthens this relationship, as positive sentiment encourages increased investment activity (Baker, M., & Wurgler, J. (2007). The research findings suggest that the decision-making quality of Indian investors is still low, partly due to the limited range of proxies utilized (Kim et al., 2022; Kumari & Mahakud, 2015). Future studies need to include daily data and more variables while considering behavioral biases, especially in various market conditions, to offer a more thorough understanding of how investor sentiment affects stock market returns.

Implications of the Study

For Investors: This research emphasizes the significance of integrating investor sentiment when making decisions. Contrarian strategies that go against prevailing sentiment could be profitable due to the inverse relationship between sentiment and market returns. Investors should remain vigilant for possible market overreactions when sentiment is high, as this can bring both chances and dangers.

For policymakers: The findings of this study can help policymakers create rules to control market volatility driven by sentiment. Successful strategies involve educating investors and improving transparency through increased disclosure. Policymakers must also take into account the impact of their decisions and messages on investor confidence and the stability of the market.

Finance professionals: They have the opportunity to enhance risk management and optimize returns by incorporating sentiment analysis into their strategies. The research highlights the importance of behavioral finance principles in emerging markets, proposing that sentiment indicators should be added to conventional financial models to improve market timing and asset allocation, all while recognizing the constraints of sentiment measures.

Scope for Future Research

1. The study can be extent by introducing more proxy variables such as social media trends, news sentiment analysis and even more sophisticated macroeconomic indicators to improve on the forecasting capabilities of the models.
2. A study analysing how overconfidence, loss aversion and, herding behavior, as examples of behavioral biases influence investors' thoughts and volatility of returns in stock market under different circumstances and market environments.
3. Future study could examine the impact of investors' sentiment on specific sectors within the Nifty 50, investigating which sectors are more prone to sentiment driven market volatility.

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