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Unveiling the Pulse of the Market: Exploring Investor Sentiment and Stock Market Volatility in India

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Abstract

Noise traders' propensity to emotionally react to market fluctuations, news, rumours, or other non-fundamental factors influences the irrational investor's financial decisions. This ultimately impacts the stock market return and volatility. To measure the irrational traders' sentiments, the study suggested the Investor Sentiment Index, which is reliable, consistent, and measures the effects on the stock market. The study incorporates daily data, as modelling volatility with high-frequency data is more accurate. The GARCH (1.1), GJR-GARCH (1.1), and E-GARCH (1.1) models were used in the study to determine how sentiment affected conditional volatility. The findings supported the presence of the leverage effect and volatility persistence. Hence, investor sentiments play a vital role in financial decisions and impact market volatility. The study supports the behavioural finance model asset pricing theory instead of traditional approaches like the capital asset pricing model, wherein the market decisions are based on fundamental information. The study will benefit policymakers and investors.

Keywords: Investor Sentiment Index, Indian Stock Market, Volatility, Return, GARCH
JEL Classifications: G12, G41

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1. Introduction

Behavioral finance is a discipline that integrates principles from psychology and economics to understand how sentiments, emotions, rumors, and psychological factors affect financial investment decisions and market volatility. The field of behavioral finance acknowledges that people frequently display cognitive biases, emotional reactions, and social influences that can result in illogical financial decision-making. It replaces the traditional approach given by Lintner (1964) as well as by Sharpe (1964), i.e., Capital Asset Pricing Models and Markowitz (1952) i.e., the Mean-Variance Portfolio Theory of finance, where financial decisions are logical and depend on fundamental and technical analysis that will optimize their economic well-being.

In behavioral finance, an investor who makes judgments regarding purchasing and selling financial assets based on impulsive or illogical considerations rather than a comprehensive examination of basic data or market patterns is known as a noise trader (Herve et al., 2019). Noise traders' propensity to emotionally react to market fluctuations, news, rumors, or other non-fundamental factors influences their preferences for specific stocks. Theoretically, irrational behavior includes noise; irrational traders perceive noise as information. It's interesting to consider that proponents of an efficient market suggested that rational arbitrageurs took advantage of noisy traders to push prices toward basic equilibrium levels. The strategies of rational arbitrageurs led to the over- or under-pricing of equities during times of low and high sentiment, and this constitutes the way noise developed (Baker & Wurgler, 2006; Lemmon & Portniaguina, 2006).

In terms of rational and irrational investor interaction, researchers have not been able to offer a sufficient framework. Despite concentrating largely on the part that noise traders play in anticipated asset yields and return volatility, a recent study on the matter significantly contributes to the literature. Many minor occurrences have created noise, which has an unpredictable effect on the market. Investors from advanced nations perform this activity because they believe that their irrational investing behaviors are to blame for the systemic risk and return anomaly (Brown & Cliff, 2004; Lemmon & Portniaguina, 2006). Based on this theoretical framework, the study investigates the contribution of irrational investor emotions to the volatility of the Indian stock market.

In 2008, the National Stock Exchange (NSE) introduced the "Volatility Index India" or "VIX." The NSE adopted the methodology initiated by the Chicago Board Options Exchange Volatility Index (CBOE VIX) in 1993. The usage of CBOE VIX as a measure of sentiment index is also witnessed by Smales (2017). The study has covered a period from 1990 to 2015. Researchers have revealed that sentiments have a bigger impact, particularly during recessions. Using a variety of sentiment indicators, the study has shown a strong link between return and investor sentiment. The term "Volatility Index India," often known as "India VIX," refers to a gauge of the Nifty 50 Index options' anticipated volatility for the ensuing thirty days. VIX provides insight into investor mood and the anticipated volatility of the Indian stock market. It expresses how risky and uncertain the market is. An elevated India VIX may indicate that investors can expect more volatility in prices. A low India VIX, on the other hand, might point to a more stable market where investors are less likely to anticipate price volatility.

Existing literature witnessed a linkage between noise trading and investors' sentiments while making financial decisions (Chau et al., 2016; Brown, 1999). The sentiment is the all-encompassing opinion held by investors about a given financial asset or financial market that is independent of the fundamental facts and information (Antoniou et al. 2015). When opposed to the low sentiment period, an irrational trader often participates in the market during the high sentiment period. (Devault et al., 2019; Shen et al., 2017; Uygur & Taş, 2014). Due to herding behavior, the higher sentiment of noise traders leads to higher volatility in the market (Hudson et al., 2018; Bahloul & Bouri, 2016; De Long et al., 1990; Black, 1986).

Numerous studies have explored the relationship between market volatility & investor sentiments in the Bangladesh market (Rahman et al., 2013); the U.S. market (Bahloul & Bouri, 2016); the Taiwan market (Yuet al., 2014; Chuang et al., 2010); the Indian market (Kumari & Mahakud, 2016); the Malaysian market (Ya'Cob&Ya'cob, 2016); the South African market (Rupande et al., 2019), etc. Some authors contend that investors driven by sentiments are inconsequential (Black, 1986), while others assert that they have a favorable impact (Charteris&Rupande, 2017), and still others have noted the unfavorable effect on markets (Daet al., 2015). Considering all the shreds of evidence, it concludes that investor sentiment affects markets, but there is no reliable measure of investor sentiment.

Although many researchers have examined the phenomenon of investor sentiments and its impact on the stock market and have confirmed the existence of both investor sentiment and market volatility, the variety of market dynamics present in the Indian economy makes it necessary to study this phenomenon in the Indian context. The Indian stock market is affected by market dynamics such as a large number of institutional investors, retail investors, foreign investors, high-frequency traders, government policies, regulatory changes, macroeconomic developments, cultural diversity, income disparity, and the country's recent initiative to transition from a developing to a developed nation by 2047. These factors make an in-depth analysis of the Indian stock market necessary. For this reason, the Indian stock market's investor sentiment was taken into consideration in this study.

The present study suggested the Investor Sentiment Index, which is reliable, consistent, and measures the effects on the stock market. In addition, previous studies in India examined the impact of investor sentiments on monthly data (Haritha & Rishad, 2020). The current study employed daily data for the period 1 Jan 2013 to 31 Dec 2022 to give more accurate results on market volatility. Previous studies have concentrated on how investor sentiment affects investment returns; however, less information exists about how sentiment affects the conditional volatility pattern of the market (Yu &Yuan, 2011; Qiu & Welch, 2006; Lemmon &Portniaguina, 2006).

2. Literature Review

The link between market volatility, market return, and investor mood has been the subject of several empirical research studies. Sentiment indices are substantially correlated with temporal returns but cannot forecast near-term future returns (Brown & Cliff, 2004). According to evidence, investor sentiments have a major influence on cross-sectional stock returns (Baker &Wurgler, 2007). Studies also examined that the impact of investor sentiments on stock returns also differs based on profitability, age, and size (Baker &Wurgler, 2006). A high degree of investor sentiment suggests investor confidence. Due to the effect of less skilled noise traders, the study saw a deterioration in the risk-return relationship during periods of elevated sentiment (Piccoliet al., 2018; Labidi &Yaakoubi, 2016; Kumari & Mahakud, 2015; Verma & Verma, 2007).

A psychological model has been developed to assess investor sentiment to understand how investors create expectations regarding future income (Barberis et al., 1998). A behavioral framework has been formulated for measuring sentiments, which addressed the findings of underreaction & overreaction of market investors (Daniel et al., 1997). Behavioral financial models have investigated the association between investor sentiment, trading activities,andmarket volatility (Black, 1986; De Long et al., 1990). Investor sentiment in the market affects market volatility (Rupandeet al., 2019; Hessary&Hadzikadic, 2017). Investor sentiment reflects the disparity in asset distribution between the actual and perceived values (Shefrin, 2008). Existing research has found that conditional volatility in the Indian stock market is influenced by investor sentiments (Naik & Padhi, 2016; Kumari & Mahakud, 2016).

Typically, a stock market may be divided into two states: bull and bear (Chau et al., 2016; Pagan &Sossounov, 2003). To distinguish between various market situations, investor sentiment is crucial. In a bull market, there is a high degree of investor sentiment since investors typically think the rising trend will continue. On the other hand, a bear market is marked by a persistent decline in share prices (Karpoff, 1987). A bear market makes investors gloomier. In reality, it might be challenging to spot the market's peaks and troughs, determining whether the market is bearish or bullish in practice. Getting a precise picture of investor sentiment is important since it shows how investors feel about the market. A key factor in determining a market situation is a gauge of the Investor Sentiment Index.

Numerous empirical research studies over the last ten years have proposed various metrics of investor sentiment. The existing literature uses several proxies to instrument investor sentiment, such as survey-driven data or market-driven indicators. Researchers evidenced that the Consumer Confidence Index (CCI) or Consumer Confidence Surveys have a direct relationship with individual, institutional & retail investor sentiments (Schmeling, 2009; Lemmon &Portniaguina, 2006; Qui & Welch, 2004). Databases of surveyshavebeen used from Investors' Intelligence, the American Association of Individual Investors, etc. to compile investor sentiments and found to be significantly associated with stock returns (Fisher & Statman, 2000; Lee et al., 2002; Brown &Cliff, 2004, 2005). Even the Facebook Gross Happiness Index (Siagnos et al., 2014) & Market Mood Index (Chakraborty & Subramaniam, 2020) have also been used by researchers as investor sentiments.

Market-driven indicators like liquidity, which can be measured by market turnover, can be an indicator of the sentiment index (Baker & Stein, 2004). Trading volume can also be used as a proxy of investor sentiments (Bu & Pi, 2014; Lee & Swaminathan, 2000). Trade volume fluctuations can also be used as a substitute for trade volume when attempting to assess investor sentiments (Haritha & Rishad, 2020). Low trading volume suggests that investors are pessimistic, whereas high trading volume suggests that investors are optimistic about the market or the company (Chuang & Ouyang, 2010). Other proxies can be the number of new investor trading accounts (Li &Zhang,2008) and the number of Initial Public offerings (IPOs) in the stock market (Haritha & Rishad, 2020; Baker & Wurgler, 2006). Odd-lot sales andpurchases, Closed-end fund discounts (CEFD), net redemptions, etc. have also been proposed as a good substitution to estimate the sentiments (Neal & Wheatley, 1998). Numerous ratios like the put-call ratio (Finter et al., 2012; Simon & Wiggins, 2001), advance decline ratio (Brown & Cliff, 2004), proportionate change in margin borrowings (Brown & Cliff, 2004), put-call open interest ratio (Wang et al., 2006), price-to-earning ration (P/E) (Pillada& Rangasamy, 2023), share turnover ratio (Baker & Stein, 2004), market turnover ratio (Haritha & Rishad, 2020), etc.

Prior studies have demonstrated a strong relationship between investor sentiments and macroeconomic variables (Grigalitiniene&Cibulskiene, 2010). It is believed that country-specific risks have a significant impact on how the macroeconomic variables of a nation behave (Huang & Suchada, 2003). Investor sentiment can also be influenced by economic variables like inflation, interest rates of lending & borrowing, changes in industrial production, exchange rates, etc. (Sehgal et al., 2010).

Recent studies created a composite sentiment index by combining many sentiment proxies as opposed to utilizing a single variable as a proxy (Haritha & Rishad, 2020; Pandey & Sehgal, 2019; Aggarwal, 2017; Ur Rehman, 2013; Chen et al., 2010). Pillada& Rangasamy (2023) measured investor sentiments by using the composition of five proxies: trading volume, market turnover, price-earnings ratio, share turnover, and advance-decline ratio. Reis & Pinho (2020) applied the volatility index, CCI, gold bullion price, treasury bond yield, the economic indicators. Rupande et al. (2019) measured sentiments by exchange rate, treasury bill rate, the Savi Index, trading volume, prime rate, changes in trading volume, and repo rate. He et al. (2007) constructed an index by using the advance-decline ratio, market capitalization to the weighted exchange rate, P/E ratio, IPOs, new investor trading accounts, CCI, the loss index, and turnover ratio. Baker & Wurgler (2006) built a sentiment index by six proxies, i.e., CEFD, IPOs, changes in trading volume, first-day IPO return average, equity issues to total issues, and market-book ratios. The present study also constructed a composite Investor Sentiment Index.

3. Data and Methodology

3.1. Data Description

Daily data of BSE Sensex return from 1st Jan 2013 to 31st December 2022 is used. The reason for preferring daily data over weekly and monthly data is that modelling volatility with high-frequency data is always more accurate. The total daily logarithmic return on BSE Sensex is calculated by using the closing price on the current day (P_t) and the closing price on the previous day (P_{t-1}).

$$R_t = log\left(\frac{p_t}{p_{t-1}}\right) \tag{1}$$

After a lot of literature review, it is observed there is an absence of any standardized index of sentiment, so a composite sentimentindex(Sentidx1) has been constructed using the proxy's A/D Ratio (Advance Decline Ratio), MCX (Multi ICOMDEX Composite Commodity Exchange of India), P/E Ratio (Price to Earnings ratio), Turnover &VWAP (the Volume-Weighted Average Price) on the BSE. The proxies are selected based on the availability of daily data from CMIE Prowess, BSE website, investing.com, etc. The Principal Component Analysis (PCA) is a dimension reduction technique, so it is used for estimations of the composite sentiment index with chosen proxies. The purpose is to extract a common component (sentiment index), not to consider what these series measures. The derived composite sentiment index is named sentidx1. It is the first PCA of the correlation matrix of the factors:

$$\text{Sentidx1} = \beta_1 \text{A/DRatio} + \beta_2 \text{MCX} + \beta_3 \text{P/E Ratio} + \beta_4 \text{Turnover} + \beta_5 \text{VWAP} + \varepsilon \tag{2}$$

Where β is the factor loading of each proxy on the composite investors' sentiment index.

Table 1: Proxies used in Investors' Sentiment Index

Proxies	Existing Literature	Variable Definition
Advance decline Ratio (A/D Ratio)	Brown & Cliff 2004 Sehgal et al., 2009 Jitmaneeroj, 2017 Pandey & Sehgal, 2019, Pillada& Rangasamy, 2023	Proportion of advancing stocks to declining stocks on the BSE. By comparing the number of stocks that closed higher against those that closed lower, the A/D Ratio provides a comprehensive picture of market sentiment and potential trends.
Multi Commodity Exchange of India (MCX)	Reis & Pinho, 2020	The MCX iCOMDEX Composite Index comprises 8 commodity futures traded on MCX: crude oil, natural gas, aluminium, copper, lead, zinc, gold, and silver. Market participants used it as a reference benchmark for performance of Indian Commodity Markets.
Price to Earnings ratio (P/E Ratio)	He et al., 2017 Khan & Ahmed, 2019 Haritha & Rishad, 2020 Pillada& Rangasamy, 2023	Ratio of the share price of a stock to its earnings per share (EPS). A volatile P/E ratio suggests that the market sentiment regarding a company's earnings prospects is changing frequently, leading to fluctuations in its stock price relative to its earnings.
Turnover	Baker &Wurgler, 2006 Chuang et al., 2010 Rehman, 2013 Li, 2014 Kumari, 2015 Gao &Yang, 2017 Khan & Ahmed, 2019 Rupande et al., 2019 Pillada& Rangasamy, 2023,	Market turnover is defined as the trading volume divided by the number of shares listed on the stock exchange. High trading volume indicates the bullish sentiments in the market. Irrational investors are more likely to trade, and thus add liquidity, when they are optimistic and betting on rising stocks rather than when they are pessimistic and betting on falling stocks.
The Volume-Weighted Average Price (VWAP)	Rupande et al., 2019	Average price of a stock weighted by the total trading volume. When the price is below the VWAP, it indicates a bearish market, whereas a price above the VWAP signifies a bullish market. These dynamics make VWAP a useful indicator for investors to gauge market sentiment and make informed trading decisions.

Source: Author's compilation

3.2 Research Methodology

The influence of sentiment on conditional volatility was examined using the Glosten, et al. (1993) - GARCH (1.1) & the GJR-GARCH (1.1), Nelson (1991) - E-GARCH (1.1) models. Because it captures the ARCH effect and autocorrelation in variance, the lag order of (1,1) was chosen. Following the unit root test (stationary test) and ARCH-LM (heteroscedasticity test), GARCH models are calculated. For stationary testing, Kwiatkowski-Phillips-Schmidt-Shin (KPSS) &Augmented Dickey-Fuller (ADF) tests are employed. The KPSS test assumes that the series does not have a unit root, whereas the ADF test assumes that the series has a unit root. The ARCH LM test is intended to gauge the longevity of the ARCH effect. The presence of the ARCH effect is necessary.

GARCH (1,1) has been acknowledged as the most successful model for estimating volatility, although it is still unable to account for the leverage impact and asymmetry in volatility. Asymmetry in volatility refers to the fact that shocks of the same size, whether positive or negative, have differing effects on the volatility of stock market returns. Positive shocks of equal size tend to have a smaller effect on volatility than negative shocks do. The leverage effect's presence suggests unequal volatility behavior. The extensions of GARCH (1.1) models, such as the EGARCH model and GJR-GARCH model, are utilized to incorporate the leverage impact and asymmetry in volatility. It is always better to conduct a sign bias test before doing any asymmetric analysis using extended GARCH models. The results of the sign bias test will give an idea whether sign and size bias are present in volatility of return or not. The significant results of the sign bias test are a good justification for estimating asymmetric models such as EGARCH and GJR-GARCH. The regression equation for the sign bias test is:

$$\hat{u}_t^2 = \phi_0 + \phi_1 S_{t-1}^- + \phi_2 S_{t-1}^- \hat{u}_{t-1} + \phi_3 S_{t-1}^+ \hat{u}_{t-1} + v_t \qquad (3)$$

Where $\hat{u}_t^2$denotes the squared residuals of GARCH model, ϕ_0 is constantS_{t-1}^- is dummy variable that takes value 1 if $\hat{u}_{t-1}$ is less than 0 & zero otherwise, $S_{t-1}^+$is defines as $1S_{t-1}^-$, $v_t$is the error term. If ϕ_1 is significant then, sign biasedness is present. If either ϕ_2 or $\phi_3$is significant, then size biasedness is also present.

While using GARCH models, the composite sentiment index, sentidx1, is added to the variance equation. It is done to investigate the role of investor sentiments in explaining volatility in BSE Sensex returns. The ADF, KPSS, and ARCH-LM tests, respectively, are used to examine the persistence of the unit root and heteroscedasticity in a data series prior to estimating the GARCH models. The same mean equation that captures the relevance of risk premium to hedge risk is used in all GARCH models, along with conditional variance. It is stated that the mean equation is:

$$y_t = \mu + \alpha y_{t-1} + \beta h_t + \varepsilon_t \qquad (4)$$

Where y_t stands for index return, α for past return's effect and β for a risk premium.

The conditional variance for the GARCH (1,1), GJR-GARCH (1,1), and EGARCH (1,1) is modelled as follows:

Model-1: Sentiment Augmented GARCH models

$$h_t = \omega + \alpha\, \varepsilon^2_{t-j} + \beta\, h_{t-i} + \varphi\, \Delta \text{Sentidx1}_t \qquad (5)$$

$$h_t = \omega + \alpha\, \varepsilon^2_{t-1} + \beta\, h_{t-j} + \gamma\, \varepsilon^2_{t-1}\, d_{t-1} + \varphi\, \Delta \text{Sentidx1}_t \qquad (6)$$

$$\log (h_t) = \omega + \alpha \left[\frac{\varepsilon_{t-j}}{\sqrt{h_{t-j}}} - E\left(\frac{\varepsilon_{t-j}}{\sqrt{h_{t-j}}}\right)\right] + \gamma_k \frac{\varepsilon_{t-k}}{\sqrt{h_{t-k}}} + \beta\, h_{t-i} + + \varphi\, \Delta \text{Sentidx1}_t \qquad (7)$$

Model-2: Sentiment Augmented GARCH models with Covid-19 period as dummy variable.

Covid-19 influences a portion of the study's period. At the time, the market was quite unpredictable. The variance equation involving the sentiment index also includes a dummy variable called 'dcovid,' which is used to show how covid-19 influences volatility.

$$h_t = \omega + \alpha\, \varepsilon^2_{t-j} + \beta\, h_{t-i} + \varphi\, \Delta Sentidx1_t + \lambda\, dcovid \tag{8}$$

$$h_t = \omega + \alpha\, \varepsilon^2_{t-1} + \beta\, h_{t-j} + \gamma\, \varepsilon^2_{t-1} d_{t-1} + \varphi\, \Delta Sentidx1_t + \lambda\, dcovid \tag{9}$$

$$\log (h_t) = \omega + \alpha \left[\frac{\varepsilon_{t-j}}{\sqrt{h_{t-j}}} - E\left(\frac{\varepsilon_{t-j}}{\sqrt{h_{t-j}}}\right)\right] + \gamma_k \frac{\varepsilon_{t-k}}{\sqrt{h_{t-k}}} + \beta\, h_{t-i} + + \varphi\, \Delta Sentidx1_t + \lambda\, dcovid \tag{10}$$

Here, h_t is the conditional variance in all the equations. Both the E-GARCH and GJR-GARCH models are used to identify the leverage effect in the data series. A positive value of γ in GJR-GARCH model (Equation (5)) indicates the leverage effect. However, as all parameters must satisfy the non-negativity criterion, non-negativity restrictions of the GJR-GARCH model may be violated, i.e., $\alpha>0$, $\beta>0$, $\omega>0$, and $\alpha+\gamma.>=0$, but the model is still applicable, even if $\gamma<0$, provided that $\alpha+\gamma.>=0$. In EGARCH model, the log of conditional variance makes the leverage effect exponential, so there is no need to impose the condition of non-negativity constraints in this model. The E-GARCH has exposed the leverage effect when $\gamma<0$.Schwartz's Bayesian criterion (SBIC), Akaike information criterion (AIC), Log Likelihood (LL), and Hannan and Quinn's criterion (HQ) are used to determine which model is the best.

4. Results and Discussions

The sequence of integration of two series—the BSE Sensex return and the Investor Sentiment Index—is shown in Table 2's findings of the stationary test (unit-root test). The level of integration of the sentiment index, Sentidx1 is 1(1) so there is a need to adjust it by taking the first difference of it, as using it in the GARCH model without taking the first difference of the series to make it stationary would give misleading results. The Sensex return series, Return, is 1(0), so this series can be used in the current form in the GARCH model.

Table 2: Results of the Stationary Test

Test			**Sentidx1**	**Return**
ADF	Level	Intercept	-0.985914	-17.62148
		Trend & Intercept	0.317616	-17.61927
	Ist Difference	Intercept	-37.4436	-21.01841
		Trend & Intercept	-37.4365	-21.01404
KPSS	Level	Intercept	5.677488	0.0345671
		Trend & Intercept	0.455135	0.028234
	Ist Difference	Intercept	0.074774	0.090554
		Trend & Intercept	0.073889	0.089198
Order of Integration			1(1)	1(0)

Source: Author's compilation

Arch-LM Effect

ARCH-LM test is applied to the return series to test the heteroscedasticity and presence of the ARCH effect in the return series. A significant ARCH effect will confirm the volatility modelling through the GARCH model. Here in Table 2, the obs* R-squared value is 80.16064 which is highly significant at a 1% significance level. Resid^2(-1) (lag value of squared residual) is also greater than 0. This indicates the presence of the ARCH effect in the BSE return series. These results indicate that we can further estimate GARCH models using these series. This is also evident from Figure 1a & Figure 1b, which show the volatility clustering.

Figure 1: BSE Sensex Returns and Residuals

Figure 1a

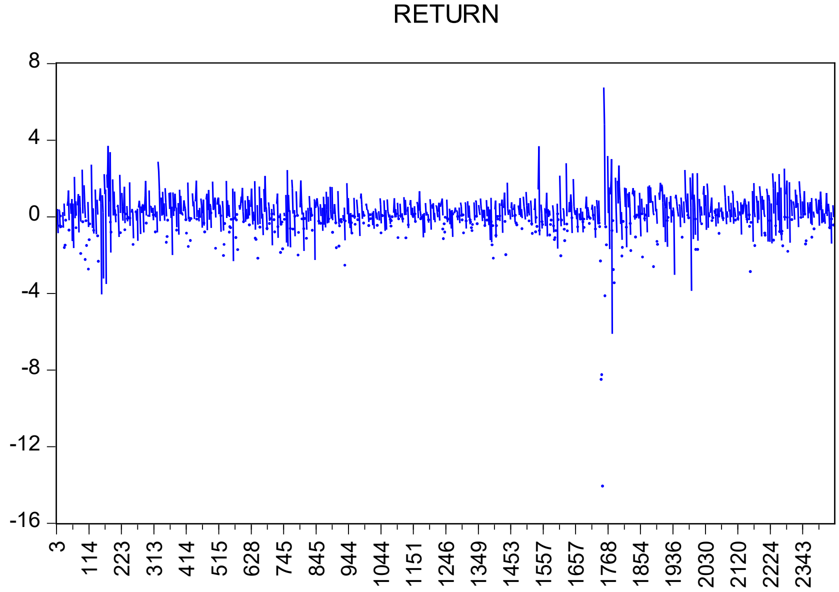
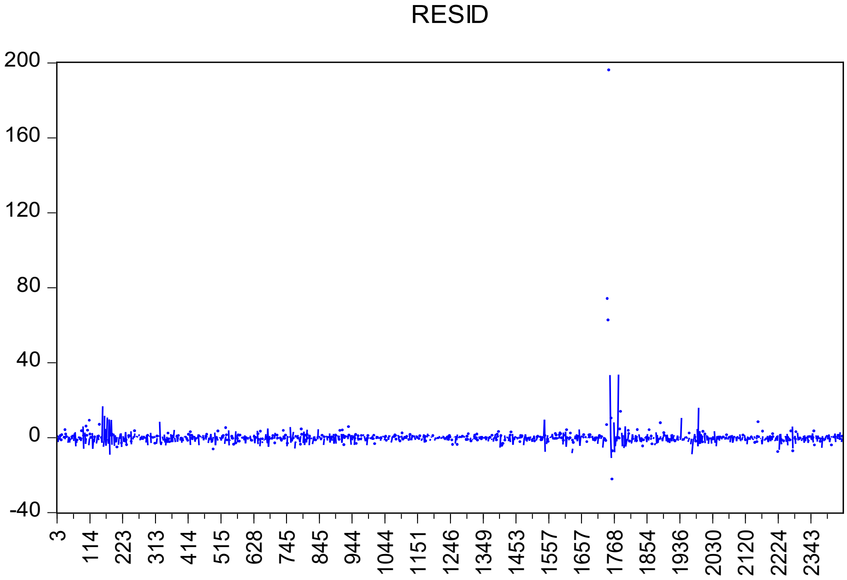


Figure 1b



Source: Author's calculations

Sign Biased Test

The co-efficient for S_{t-1}^{-}, ϕ_1, is significant at the 5% significance level. It is a strong indicator of sign bias. The co-efficient of $S_{t-1}^{-}\hat{u}_{t-1}$ and $S_{t-1}^{+}\hat{u}_{t-1}$i.e. $\phi_2$and ϕ_3 are also significant at 5% level. These are the strong indicators of size bias. The test results serve as a good justification for estimating GARCH models, which allow for asymmetric volatility.

Table-3: Results of Sign Bias Test

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.854635	0.223859	-3.81774	0.00010
S^{-}_{t-1}	(ϕ1)1.420099	0.302217	4.698934	0.00000
$S^{-}_{t-1}\hat{u}_{t-1}$	(ϕ2)0.818715	0.173419	-4.721022	0.00000
$S^{+}_{t-1}\hat{u}_{t-1}$	(ϕ3)2.863077	0.219968	13.01587	0.00000

Source: Author's compilation

GARCH Estimates

The information criteria results for Model-1 and Model-2 are presented in Table 4. In Model-1, EGARCH-M is the best model whereas in Model-2, GJR-GARCH-M is the best model. According to Mandimika &Chinzara (2012), Table 5 shows that the E-GARCH-M model does not satisfy the stationary criterion, where α+β<0. This conclusion suggests that a future shock will last for an extended length of time and be followed by extremely high volatility. The GJR-GARCH-M model is therefore applicable based on information criteria and stationary conditions. In both Model-1 (sentiment augmented GARCH model) and Model-2 (sentiment augmented GARCH model with the Covid-19 period as a dummy variable) GJR-GARCH-M is the best-suited model for modelling conditional volatility.

Table 4: Results Information Criteria for Sentiment augmented GARCH models with or without Covid-19 Effect

MODEL	Model-1: Sentiment Augmented GARCH model without Covid-19 effect			Model-2: Sentiment Augmented GARCH model with Covid-19 effect		
	GARCH-M sentidx1	GJR-GARCH-M sentidx1	EGARCH-M sentidx1	GARCH-M sentidx1&dcovid	GJR-GARCH-M sentidx1 & dcovid	EGARCH-M sentidx1 & dcovid
AIC	2.691954	2.650085	2.647598	2.691065	2.648403	2.690719
SC	2.708604	2.669114	2.666627	2.710093	2.669810	2.709747
HQ	2.698007	2.657003	2.654515	2.697982	2.656184	2.697636
LL	3274.492	--3222.454	-3219.422	-3272.408	- 3219.403	-3271.986

Source: Author's calculations

The result of the GARCH models' mean equation demonstrates that returns may be explained by their past returns. Although the variance term GARCH in the mean equation of the GARCH model is not statistically significant, its inclusion in the mean equation has significantly boosted the relevance of the GARCH term in the variance equation. The risk is reflected by volatility, and the GARCH term is large in the variance equation (EViews10), which suggests that the risk premium is not a meaningful risk hedge when investing in shares.

The conditional mean might depend on its conditional variance as well as other factors when using the GARCH-M, referred to as the GARCH-in-mean model. All the measurement parameters in the variance equation of both Model-1 and Model-2 can be seen to be statistically significant, except in EGARCH-M model, which shows sentiments have no significant effect on the volatility of BSE Sensex returns. It may be because the EGARCH model fails to satisfy stationary conditions, and it results in explosive volatility. Sentiments are also difficult to capture in case of explosive volatility. The GJR-GARCH-M model with sentiment augmentation is stationary as α+β+γ/2<1, indicating that volatility is quite persistent. Returns volatility across the research period can be attributed to past shocks α, prior volatility β, and investor sentiments Ø. According to Table 5 findings, the sentiment-enhanced GJR-GARCH-M model's leverage effect value γ is considerably positive (Chinzara &Aziakpano, 2009). This indicates that compared to positive shocks of the same magnitude and strength, negative shocks have a greater influence on volatility. The coefficient for the dummy variable (λ) for Covid-19 is also significant. It means Covid-19 has a significant role in modeling conditional volatility.

Table 5: GARCH Specifications in the variance equation

MODEL	**Model-1: Sentiment Augmented GARCH model without Covid-19 effect**			**Model-2: Sentiment Augmented GARCH model with Covid-19 effect**		
Variance Equation	GARCH-M sentidx1	GJR-GARCH-M sentidx1	EGARCH-M sentidx1	GARCH-M sentidx1 &dcovid	GJR-GARCH-M sentidx1 &dcovid	EGARCH-M sentidx1 &dcovid
C	0.026224*	0.035276*	-0.109701*	0.040210*	0.048490*	-0.08818*
A	0.092425*	-0.013042*	0.134672*	0.091697*	-0.013063**	0.123276*
B	0.884305*	0.884621*	0.964403*	0.880146*	0.879607*	0.958874*
Γ		0.182949*	-0.127207*	-	0.185419*	-0.137376
Ø	-0.247974*	-0.232207*	-0.175365	-0.244224*	-0.230047*	-0.188500
Γ	-	-	-	-0.013292*	-0.013516*	-0.020333*
α + β			1.099075			1.08215
α+β+γ/2<1		0.9630535			0.959253	

*Note: * Values are significant at a 5% significance level, **Values are significant at a 10% significance level*

Source: Author’s calculations

It can be noted here that investor sentiments have a negative effect on conditional volatility, as all Ø values are negative and significant. It means noise traders exit the market when there are low sentiments. As a result of their diminished influence on the market, there is less market volatility. When market sentiments are high, noise traders become more active, increasing their effect on the market as well as market mispricing, which results in excessive volatility.

5. Conclusion

The study analyzed the role of investor sentiments on stock market volatility by using daily data over the period 1st January 2013 to 31st December 2022 for BSE Sensex returns. The GARCH model augmented by a sentiment index is used to model volatility. The sentiment index is generated from five proxies, i.e., A/D Ratio (Advance Decline Ratio), MCX (Multi Commodity Exchange of India), P/E Ratio (Price to Earnings ratio), Turnover & VWAP (Volume-Weighted Average Price) on the BSE using PCA technique. The results show that BSE Sensex return is affected by their past return. The inclusion of variance in the mean equation has no significant result in the mean equation, but it makes the variance equation more powerful. It is concluded here that risk premium is not significant to hedge risk for holding assets. Based on information criteria and stationary conditions, the GJR-GARCH-M model was chosen to model volatility in returns. Based on the model specification, the volatility persistence and leverage effect are found. Investor sentiments are considered a significant factor in explaining the conditional volatility in BSE SENSEX. The research validates the finding of previous researchers that there is a substantial relation between investor sentiments and volatility in the Indian stock market (Chandra & Thenmozhi, 2013; Kumari & Mahakud, 2016; Naik & Padhi, 2016). Covid-19 played a significant role in volatility modeling. Hence, it confirms that irrational investor emotions have a role in the Indian stock market's volatility (Brown & Cliff, 2004; Lemmon & Portniaguina, 2006).

The study proved that investor sentiments play a vital role in financial decisions and impact market volatility. The research reinforces the contention stated by Herve et al. (2019) that "noise trading" is a real-life phenomenon that leads to irrational trading. The study supports the behavioral finance model asset pricing theory instead of traditional approaches like the capital asset pricing model, wherein the market decisions are based on fundamental information (Rupandeet al., 2019; Hessary & Hadzikadic, 2017; De Longet al., 1990; Black, 1986). Adverse shocks lead to fluctuations in investor sentiment, which creates strong volatility. Investors' emotions enacted due to any new information, media coverage, or news can play an important role in forecasting the market trends.

The study additionally addresses the potential for future development. For instance, it used the BSE Sensex index to measure the effect of investor sentiment on volatility, although attitudes may differ for various industry sectors or companies and have a different influence on volatility and returns. Additionally, although the study is restricted to India, it may be expanded to include other Asian nations. Due to the lack of a direct measure of the investor sentiment index in the Indian market, the study employed sentiment proxies to quantify the impact of emotions/moods/feelings on volatility. Although several alternative proxies for emotion have been discussed in the literature, the lack of daily data proved a limitation. To see whether the same outcomes are obtained in other Asian markets, the study can be reproduced.

Research Limitations

The study will benefit policymakers and investors. When developing or enacting new strategies or policies, policymakers must consider the influence that any new information, media coverage, or news will have on investors' emotions. As volatility increases, regulators must pay more consideration to adverse shocks and changes in investor sentiment. As adverse shocks lead to more fluctuations in investor sentiment, which creates high volatility. The results are vital for regular investors and portfolio managers who aim to put together the optimal portfolio achievable for maximizing profits.

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