INVESTOR SENTIMENTS AND STOCK MARKET VOLATILITY: EVIDENCE FROM 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.

Key Words: Investor Sentiment Index, Indian Stock Market, Volatility, Return, GARCH

Introduction:

Behavioral finance is a discipline that integrates principles from psychology and economics to understand how sentiments, emotions, rumours, 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, depend on fundamental & 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, rumours, 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.

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 (Yu, J., et al., 2014; Chuang, et al. 2010); Indian market (Kumari & Mahakud, 2016); Malaysian market (Ya'Cob & Ya'cob, 2016); South African market (Rupande, L. et. al., 2019), etc. Some authors contend that investors driven by sentiments are inconsequential (Black, 1986), while others assert that they have a favourable impact (Charteris, A., & Rupande, L., 2017), and still, others have noted the unfavourable effect on markets (Da, Larrain, et. al., 2015). Considering all the shreds of evidence concludes that investor sentiment affects markets but there is no reliable measure of investor sentiment.

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 and Yuan, 2011, Qiu & Welch, 2006; Lemmon & Portniaguina, 2006).

Literature Review:

The link between market volatility, market return, and investor mood has been the subject of several empirical research. 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 and Wurgler, 2007). Studies also examined that the impact of investor sentiments on stock returns also differs based on profitability, age, and size (Baker and 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 (Piccoli, D. et. 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., 1998). Behavioral financial models have investigated the association between investor sentiment trading activities & market volatility (Black, 1986; De Long, et al., 1990). Investor Sentiment in the market affects market volatility (Rupande, L. et 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 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; Ho & Hung, 2008; Lemmon & Portniaguina, 2006; Qui & Welch, 2004). Database of survey has been used from the Investors’ Intelligence, the American Association of Individual Investors, etc. to compile investor sentiments and found significantly associated with stock returns (Fisher & Statman, 2000; Lee et al., 2002; Brown and 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 (Hui & Li 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 and Zhang; 2008) and the number of Initial Public offerings (IPOs) in the stock market (Haritha & Rishad, 2020; Baker et al., 2012). Odd-lot sales & purchases, 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 & Ruenzi 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. (Haritha & Abdul, 2020; 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 bonds yield, the economic indicators. Rupande, L. 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) build 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.

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, 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}).

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

After a lot of literature review it is observed there is an absence of any standardized index of sentiment so, a composite sentiment index (Sentidx1) has been constructed using the proxy's A/D Ratio (Advance decline Ratio), MCX (Multi 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 dimensions 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:

$$\text{Sentidx1} = \beta_1 \text{ A/D Ratio} + \beta_2 \text{ MCX} + \beta_3 \text{ P/E Ratio} + \beta_4 \text{ Turnover} + \beta_5 \text{ Vwap} + \varepsilon \qquad (2)$$

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	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 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 and Wurgler, 2006 Chuang et al. 2010 Rehman, 2013 Li 2014 Kumari, 2015 Gao and 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: Authors' Compilation

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) model. 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-Schmidh-Shin (KPSS) & the 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 extension 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.

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:

$$y_t = \mu + \alpha\, y_{t-1} + \beta\, h_t + \varepsilon_t \qquad (3)$$

Where y_t stands for index return, α for past return's effect & 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:

$$h_t = \varpi + \alpha\, \varepsilon^2_{t-j} + \beta\, h_{t-i} + \varphi\, \Delta Sentidx1_t \qquad (4)$$

$$h_t = \varpi + \alpha\, \varepsilon^2_{t-1} + \beta\, h_{t-j} + \gamma\, \varepsilon^2_{t-1}\, d_{t-1} + \varphi\, \Delta Sentidx1_t \qquad (5)$$

$$\log(h_t) = \varpi + \alpha \left[\frac{\varepsilon_{t-j}}{\sqrt{h_{t-j}}} - E\left(\frac{\varepsilon_{t-j}}{\sqrt{h_{t-j}}}\right)\right] + \gamma_k \frac{\varepsilon_{t-k}}{\sqrt{h_{t-k}}} + \beta\, h_{t-i} + + \varphi\, \Delta Sentidx1_t \qquad (6)$$

Here, h_t is the conditional variance in all the equations. A positive value of γ in Equation (5) indicates the leverage effect. Both the E-GARCH and GJR-GARCH models are used to identify the leverage effect in the data series. 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 $\alpha+\gamma.>=0$. The E-GARCH has exposed the leverage effect when $\gamma<0$. The model is still applicable, even if $\gamma<0$, provided that $\alpha+\gamma.>=0$. EGARCH model in Equation (6) uses log values and overcomes the issue of non-negativity constraints. Since the leverage effect is exponential in assessing the log of the conditional variance under the EGARCH model, it is guaranteed that the estimations of conditional variance cannot be negative. 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.

Results and Discussions

Equation (2) shows the principal component analysis method's Sentidx1 composite sentiment index. The factor loadings of all the proxies are placed into the equation.

The sequence of integration of two series—the BSE Sensex return and the Investor Sentiment Index—is shown in Table 1'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

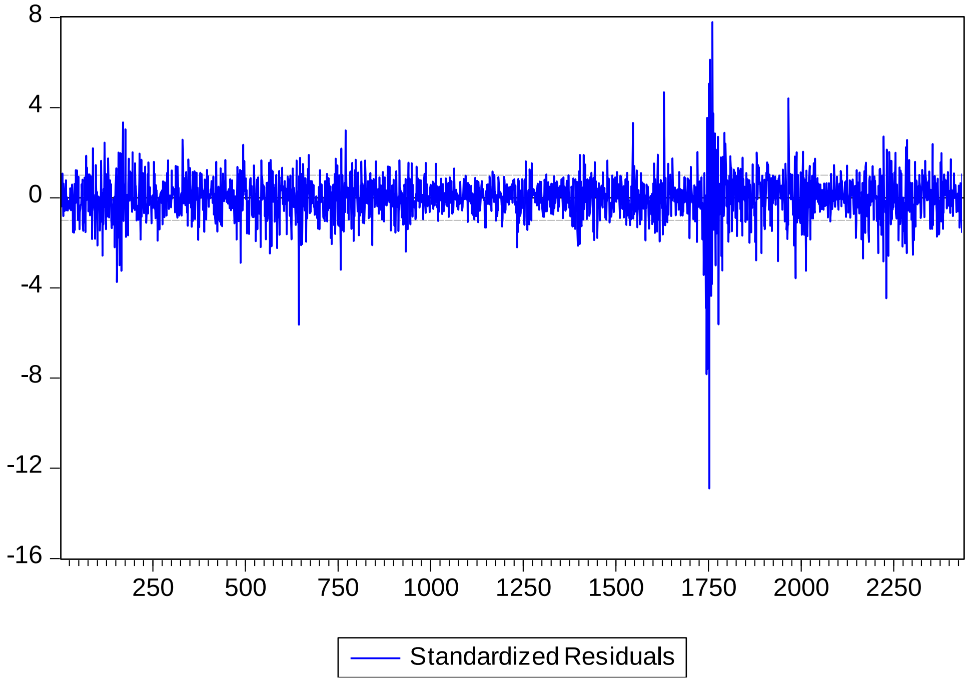
Test			Sentidx1	Return
ADF	Level	Intercept	-0.985914	-17.62148
		Trend & Intercept	0.317616	-17.61927
	Ist Difference	Intercept	-37.4436	-21.01841
		Trend & Intercept	-37.4365	-21.01404
KPSS	Level	Intercept	5.677488	0.0345671
		Trend & Intercept	0.455135	0.028234
	Ist Difference	Intercept	0.074774	0.090554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

*Author’s Compiled Source

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 the above table, 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 1 where most also show the volatility clustering

Figure-1: BSE Sensex Returns



The information criteria result from Table 2 reveals that the three GARCH specifications that best depict the BSE Sensex return conditional volatility are E-GARCH-M, GJR-GARCH-M, and plain GARCH-M. According to Mandimika and Chinzara (2012), Table 3's model results show that the E-GARCH model does not satisfy the stationary criterion, where $\alpha+\beta<0$. 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 criterion and stationary condition.

Table 3: Results Information Criteria for Sentiment augmented GARCH models

	GARCH- M sentidx1	GJR-GARCH-M sentidx1	EGARCH- M sentidx1
AIC	2.691954	2.650085	2.647598
SC	2.708604	2.669114	2.666627
HQ	2.698007	2.657003	2.654515

LL	-3274.492	--3222.454	-3219.422

*Author's Compiled Source

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 of the measurement parameters in the variance equation can be seen to be statistically significant, except the EGARCH-M sentidx1 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 $\alpha+\beta+\gamma/2<1$, 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-3 findings, the sentiment enhanced GJR-GARCH-M model's leverage effect value γ is considerably positive (Chinzara and Aziakpano, 2009). This indicates that compared to positive shocks of the same magnitude and strength, negative shocks have a greater influence on volatility.

Table 4: GARCH Specifications in the variance equation

Variance Equation	GARCH- M sentidx1	GJR-GARCH-M sentidx1	EGARCH-M sentidx1
Ω	0.026224*	0.035276*	-0.109701*
A	0.092425*	-0.013042*	0.134672*
B	0.884305*	0.884621*	0.964403*
Γ		0.182949*	-0.127207*
Ø	-0.247974*	-0.232207*	-0.175365
$\alpha + \beta$			1.099075
$\alpha+\beta+\gamma/2<1$		0.9630535	

*Values are significant at a 5% significance level

Note: Author's Compiled Source

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.

Conclusion

In this paper, the authors 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. GARCH-M specification 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 (the Volume-Weighted Average Price) on the BSE using PCA technique The results shows 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 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 study proved that investor sentiments play a vital role in financial decisions and impact market volatility. Noise trading is a phenomenon that leads to irrational trading. 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. Adverse shocks leads to fluctuations in investor sentiment which creates volatility strengthens. 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 Implications

The study will benefit policymakers and investors. When developing or enacting new strategies or policies, policymakers must take into account 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 leads 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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