





“Modeling a bi-directional sentiment-return relationship: Evidence from the Indian market”

AUTHORS	Ajit Yadav  Anindita Chakraborty  Vijaya 
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Ajit Yadav, MBA, Doctoral Student,
Institute of Management Studies,
Banaras Hindu University, India.
(Corresponding author)

Anindita Chakraborty, Ph.D., Lecturer,
Institute of Management Studies,
Banaras Hindu University, India.

Vijaya, MBA, Doctoral Student,
Institute of Management Studies,
Banaras Hindu University, India.

Ajit Yadav (India), Anindita Chakraborty (India), Vijaya (India)

MODELING A BI-DIRECTIONAL SENTIMENT-RETURN RELATIONSHIP: EVIDENCE FROM THE INDIAN MARKET

Abstract

In the last two decades, the subject of investor sentiment has attracted the attention of researchers across the globe. This study attempts to examine the bi-directional relationship between investor sentiment and stock market returns in the Indian market by focusing on both contemporaneous and lagged relationships between investor sentiment and market returns. It also attempts to study the effect of lagged market returns on the current market returns. This study constructs an investor sentiment index for the Indian market using the principal component analysis technique. The results of the regression analysis between the investor sentiment index and stock market returns establish that current sentiment positively affects current market returns, and one-month lagged sentiment negatively affects current market returns. Further, it is found that a one-month lagged market return has a positive association with the current market returns. Moreover, using the VAR model, this study found the existence of a contemporaneous and lagged bidirectional relationship between investor sentiment and market returns. The results of impulse response analysis and variance decomposition analysis also support the presence of a sentiment-return bidirectional relationship but show that the effect of sentiment on market returns is more pronounced than the effect of market returns on investor sentiment.

Keywords

principal component analysis, Granger causality, vector autoregression, Geweke test, impulse response analysis, variance decomposition analysis

JEL Classification

G10, G11, G41

INTRODUCTION

Investor sentiment has grabbed the attention of scholars around the globe owing to its ability to influence stock returns, as investors are not always rational in their decision-making while selecting stocks and tend to trade on noise (Black, 1986). The traditional theory of finance (Fama, 1965) postulates that stock prices reflect the fundamental value of the securities and are not guided by the sentiments of the investors. It propounds that even if irrational traders try to deviate stock prices away from their fundamental value, rational arbitrageurs will counterbalance their demands by pushing prices back to their intrinsic value. However, the tenets of behavioral finance assert that there are limits to arbitrage (Shleifer & Vishny, 1997), while exploiting the irrationality of the investors who trade on noise and individual beliefs (De Long et al., 1990) and investor sentiment plays a vital role in determining stock prices.

Investors' optimism (pessimism) may cause mispricing in the stock market, hence, creating a significant impact on the stock returns. This leads stock prices to rise (fall) from the underlying fundamental value (Barberis et al., 1998), and investors overvalue (undervalue) asset



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prices due to their optimism (pessimism), which is not justified by the fundamentals. The impact of sentiment on returns is established across developed and emerging economies. However, the question arises whether it is only the sentiment that affects the stock returns or whether stock returns also affect the sentiment of the investors.

The studies exploring bidirectional sentiment-return relationships in the Indian context are limited and show contradictory results. Moreover, the available studies have focused only on the lagged causality and do not consider contemporaneous feedback between sentiment and stock returns (Dash & Mahakud, 2012; Dash & Maitra, 2018; Naik & Padhi, 2016). Despite its huge relevance in guiding stock markets performance, the topic of sentiment-return bidirectional relationship is under-explored and requires more attention.

1. LITERATURE REVIEW

Investor sentiment affects asset prices (Baker & Wurgler, 2006, 2007; Brown & Cliff, 2004; DeLong et al., 1990). Baker and Wurgler (2006) define investor sentiment as the “propensity of the investors to speculate stock prices” based on the “irrational exuberance” (Shiller, 2000) of the investors. Baker and Wurgler (2006) studied the US market and documented that “sentiment is a contrarian predictor of stock returns for small, young, high volatile, unprofitable, non-dividend paying, extreme growth, and distressed stocks.” Baker and Wurgler (2007) followed a “top-down approach” to measure investor sentiment and emphasized that sentiment affects both individual stocks and stock market returns, respectively.

The researchers in the domain have mixed opinions. Few researchers advocate that sentiment and returns move in opposite directions, i.e., if the sentiment is high (low), then the return is low (high) (Baker & Wurgler, 2006; 2007; McGurk et al., 2020; Rashid et al., 2019; Schmeling, 2009; Yu & Yuan, 2011; Yu et al., 2014), whereas few researchers propound that investor sentiment positively affects stock returns (Aggarwal & Mohanty, 2018; Verma & Verma, 2007; Xu & Zhou, 2018). Moreover, a group of scholars believes that investor sentiment has little or no role in predicting returns (Canbas & Kandir, 2009; Kim & Kim, 2014).

There has been an increase in the research studying the effect of sentiment on returns (Anusakumar et al., 2017; Al-Nasseri et al., 2021; Canbas & Candir, 2009; Chakraborty & Subramaniam, 2020; Chen et al., 2013; Dash & Mahakud, 2012; Huang et al., 2014; Li, 2021; Rashid et al., 2019) but subsequently,

the researchers are also focusing on the existence of two-way directionality (bi-directionality) between investor sentiment and stock returns.

Marczak and Beissinger (2016) studied the relationship between investor sentiment and stock returns using the wavelet approach that includes the identification of the lead-lag relationship. Using evidence from the S&P 500 index returns and two US sentiment indicators and covering a time span between January 1970 to September 2014, they advocate that in the short run (up to three months), the sentiment leads returns beyond which (3-36 months), returns lead sentiment, but in both cases, the sentiment-return relationship is positive but fades away with the passage of time following technical corrections.

Ugurly-Yildirim et al. (2021) gauged the US market to study the co-integrating relationship between monetary policy uncertainty, investor sentiment, and stock returns. They measured investor sentiment using Michigan Consumer Sentiment Index (MCSI). The sample period for the study was from January 1985 to September 2017. Using the nonlinear autoregressive distributed lag model, they support that (i) in the short run, there exists a negative and bidirectional relationship between monetary policy uncertainty and stock returns; (ii) the monetary policy uncertainty negatively affects investor sentiment in the long run; (iii) in the long run, as well as the short run, investor sentiment affects stock returns, and the sentiment-return association runs both ways (bi-directional), and the association is positive.

Khan and Ahmad (2018) studied the existence of contemporaneous as well as lagged bidirectionality between investor sentiment and stock market

returns in the Pakistani market from 2006 to 2016. They found that “current sentiment has a positive relationship with the current market returns, and lagged sentiment has a negative relationship with the current market returns” (p. 13). They further support the existence of a bidirectional sentiment-return relationship, but the effect of sentiment on returns is much stronger than the effect of stock market returns on sentiment (Khan & Ahmad, 2018).

Bayram (2017) studied the Turkish market to gauge the effect of rational and irrational components of sentiments of both individual and business consumers on the Istanbul Stock Exchange returns. Drawing on the sample period from December 2003 to January 2010, he found that the effect of rational sentiment (both for individual and business investors) on stock returns is more pronounced than irrational sentiment. They further documented that a strong bidirectional relationship exists between the rational sentiment of both individual and business investors and stock returns.

In the Indian context, Dash and Maitra (2018) investigated the relationship between investor sentiment and stock returns using evidence from Nifty 50 returns. The sample period of the study was April 2002 to May 2014. They found that stocks with higher returns are more prone to sentiment effect, and a strong bidirectional causality runs between investor sentiment and stocks with higher returns, such as mid-cap and small-cap stocks.

Naik and Padhi (2016) “examined the relationship between investor sentiment and stock return volatility using evidence from National Stock Exchange for the period ranging from July 2001 to December, 2013. The sentiment index is constructed using seven market-related proxies. They found that excess market returns are a function of investor sentiment. Positive and negative sentiment changes have a varied effect on the stock return volatility, and bidirectional sentiment-return relationship exists but only on the third lag” (Naik & Padhi, 2016, p. 235). On the other hand, Dash and Mahakud (2012), drawing evidence using sample period ranging from February, 2003 to March, 2011 from the BSE Sensex and Nifty sectoral indices, show that returns do not Granger-cause stock market returns.

Hence, it is evident from the literature that investor sentiment affects stock market returns. However, the consensus in regard to the effect of stock market returns on investor sentiment is still a matter of considerable debate as research in this area is limited especially in the Indian context and explores only lagged causality. Hence, it becomes imperative to explore the existence of sentiment-return bi-directionality in the Indian market.

Based on the above premise, this study examines the bidirectional relationship between investor sentiment and stock market returns in India using the VAR (vector autoregression) model. This paper models both the contemporaneous as well as lagged sentiment-return relationship in India. Further, it also studies the effect of lagged market returns on current market returns.

2. METHODOLOGY

This study employs the seven indirect sentiment proxies, namely, advance to decline ratio (ADR), price to earnings ratio (PE), share turnover (TURN), volatility premium (VOLPREM), buy-sell imbalance ratio (BSIR), equity issuance in total issuance (EITI), and turnover volatility ratio (TVR), to construct the investor sentiment index for the Indian market.

S&P BSE 500 firms constitute the sample list with a sample period ranging from April 2009 to March 2022, comprising 156 monthly observations. The data for calculating sentiment proxies are sourced from the Bombay Stock Exchange website, the PROWESSIQ database (maintained by the Centre for Monitoring Indian Economies (CMIE)), and the Securities Exchange Board of India (SEBI). The data for the macroeconomic indicators were sourced from the Reserve Bank of India website, and the data for the market return proxied by BSE 500 returns is sourced from the Bombay Stock Exchange website.

The macroeconomic variables may significantly impact the sentiment of the investors. Therefore, sentiment proxies are orthogonalized by regressing each sentiment proxy to the set of macroeconomic variables, namely Bank rate (BR), Index of Industrial Production (IIP), Foreign Institutional Investment (FII), Consumer Price Index (CPI), and Exchange Rate (EX).

$$SENT_t = \alpha + \beta_1 BR_t + \beta_2 IIP_t + \beta_3 TFII_t + \beta_4 CPI_t + \beta_5 EX_t + \varepsilon_t, \quad (1)$$

where $SENT_t$ is each sentiment proxy, and BR, IIP, FII, CPI, and EX are the macroeconomic variables against which each sentiment proxy is regressed. The residuals of each regression analysis (shown in equation 1) for each sentiment proxy illustrate the irrational sentiment component, which is treated as orthogonalized sentiment proxies for further calculations.

The study uses a two-stage process to develop the sentiment index. Firstly, the provisional sentiment index is created, and the final sentiment index is later obtained. The study first uses the principal component analysis on the current and lagged values of orthogonalized sentiment proxies to obtain the provisional sentiment index. The coefficient for each proxy is the first principal component that explains the greatest variation.

Further, the correlation coefficient is estimated between each sentiment proxy's current or lagged values with the provisional sentiment index. Finally, the proxy's current and lag values, whichever has a higher correlation with the provisional sentiment index, are used to construct the final sentiment index $SENT_t$ using the first principal component as shown in equation 2.

$$SENT_t = \alpha + \beta_1 ADR_{t-i} + \beta_2 PE_{t-i} + \beta_3 TURN_{t-i} + \beta_4 VOLPREM_{t-i} + \beta_5 BSIR_{t-i} + \beta_6 EITI_{t-i} + \beta_7 TVR_{t-i} + \varepsilon_t. \quad (2)$$

Using the Augmented Dickey-Fuller (ADF) (Dickey & Fuller, 1979, 1981) and Phillips-Perron (PP) (Phillips & Perron, 1988) tests, the stationarity of the time series was examined. Both tests are administered at the level and at the first difference for both constant and constant with a time trend.

Investor sentiment affects contemporaneous stock market returns (Baker & Wurgler, 2006; Brown & Cliff, 2004), but the effect of sentiment could also occur with the time lag. Further, past stock market returns could also influence present returns. Hence, the study uses the following regression equation:

$$RM_t = \alpha + \beta SENT_t + \sum_{i=1}^p \alpha_i SENT_{t-i} + \sum_{i=1}^q \beta_i RM_{t-i} + \varepsilon_t, \quad (3)$$

where RM_t and RM_{t-i} are the market return at time t and at selected lag time-interval, respectively. $SENT_t$ and $SENT_{t-i}$ denote the sentiment index at time t and selected time-lag, respectively. p and q are the lag lengths selected according to AIC (Akaike's information criterion) and SIC (Schwarz Information Criterion) criteria.

Further, the relationship between investor sentiment and stock returns may be two-way (bi-directional), as returns could also shape the sentiment of the investors, either contemporaneously or with a time lag. Hence, to assess the directionality of the sentiment-return relationship in the Indian market, this study uses the VAR (vector autoregression) model. The general form of a simple bivariate VAR model with no intercept is:

$$\begin{pmatrix} RM_t \\ SENT_t \end{pmatrix} = \begin{pmatrix} \alpha_{10} \\ \alpha_{20} \end{pmatrix} + \sum_{i=1}^p \begin{pmatrix} a_{11}(i) & a_{12}(i) \\ a_{21}(i) & a_{22}(i) \end{pmatrix} \begin{pmatrix} RM_{t-i} \\ SENT_{t-i} \end{pmatrix} + \begin{pmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{pmatrix}. \quad (4)$$

VAR model can be used to describe the joint occurrence process of two or many variables across time. VAR-based Granger causality test (Granger, 1969) helps determine whether one time series can help forecast another time series. The Granger-causality statistics are F-statistics that determine if all of a variable's lag coefficients in an equation involving another variable are collectively equal to zero. As the p-value of the F-statistic decreases, it confirms that the variable is important for predicting another variable. The general form of the bivariate linear autoregressive model, which tests for granger causality, is:

$$RM_t = \sum_{i=1}^p a_{11i} RM_{t-i} + \sum_{i=1}^p a_{12i} SENT_{t-i} + \varepsilon_{1t}, \quad (5)$$

$$SENT_t = \sum_{i=1}^p a_{21i} RM_{t-i} + \sum_{i=1}^p a_{22i} SENT_{t-i} + \varepsilon_{2t}, \quad (6)$$

where p is the lag order, the matrix α denotes the model coefficients, RM_t and $SENT_t$ are the two

variables at time t , and ε_1 and ε_2 are the residuals (error term). If the variance of ε_1 (or ε_2) decreases with the inclusion of the *SENT* (or *RM*) terms in equation no. 5 or 6, then it is said that *RM* (or *SENT*) Granger causes *SENT* (or *RM*).

Granger causality is not necessarily true causality (Maziarz, 2015), as it only points out the simple existence or absence of causality between two variables. Further, it only accounts for lagged responses and does not consider the contemporaneous relationship. Hence, to account for the contemporaneous bidirectional relationship between investor sentiment and stock market returns, this study employs Geweke's procedure (Geweke, 1982). Geweke's approach is based on a linear feedback mechanism, i.e., a linear feedback measure from variable X to variable Y, a linear feedback measure from Y to X, and an instantaneous linear feedback measure between variables X and Y. Details of Geweke's approach are shown in Appendix 1.

Also, the Impulse response function in time series traces the dynamic path of variables in the system in response to the shocks to other variables in the system with the help of the VAR model. Finally, the forecast error variance is attributable to each model variable using forecast error decomposition. This metric aids in determining the degree of influence one variable have on another in the VAR model and the degree of interdependence between the variables.

3. EMPIRICAL RESULTS

Each sentiment proxy, namely, advance to decline ratio (ADR), price to earnings ratio (PE), share turnover (TURN), volatility premium (VOLPREM), buy-sell imbalance ratio (BSIR), equity issuance in total issuance (EITI), and turnover volatility ratio (TVR) have been first standardized using Z-score to normalize it and bring it to the same scale before constructing the investor sentiment index. The details of the sentiment proxies can be found in Appendix 26 including their detailed explanation. Appendix 3 shows the descriptive statistics of the standardized sentiment proxies with their inter-item correlations. Moreover, the study adjusts sentiment proxies to the macroeconomic variables, namely bank rate, industrial

production index, foreign institutional investors, consumer price index, and exchange rate.

Further, to ensure that the sample is fit for the application of principal component analysis, the KMO measure of sampling adequacy and Barlett's test of sphericity are estimated. The value of KMO is 0.645 (which is greater than 0.6), and Barlett's test of sphericity has a significance level of 0.000, implying that the sample is adequate. PCA technique is applied to the proxies and their one-month lag, and the first principal component is taken as the coefficients of the proxies and their lags because (i) the first principal component explains 63% (highest) of the variation, (ii) the second principal component contains eigenvalues with negative coefficients. Hence first principal component is selected as the coefficient of proxies and their lags to construct a provisional sentiment index.

3.1. Sentiment index

The provisional sentiment index, which contains all the seven proxies current and lagged values, is represented as PROVSENT.

$$\begin{aligned}
 \text{PROVSENT} = & 0.241\text{ADR}_t + 0.088\text{BSIR}_t + \\
 & +0.440\text{EITI}_t + 0.237\text{VOLPREM}_t + \\
 & +0.615\text{TURN}_t + 0.315\text{PE}_t + 0.714\text{TVR}_t + \quad (7) \\
 & +0.513\text{ADR}_{t-1} + 0.293\text{BSIR}_{t-1} + \\
 & +0.330\text{EITI}_{t-1} + 0.154\text{VOLPREM}_{t-1} + \\
 & +0.719\text{TURN}_{t-1} + 0.258\text{PE}_{t-1} + 0.633\text{TVR}_{t-1}.
 \end{aligned}$$

Further, the correlation between the *PROVSENT* and the orthogonalized sentiment proxies and their lags are computed, which is shown in Table 1.

Table 1. Correlation coefficient between *PROVSENT* and contemporaneous and lag value of sentiment proxies

Source: Authors.

ADR_t	BSIR_t	EITI_t	VOLPREM_t	TURN_t	PE_t	TVR_t
0.252 (0.00)	0.084 (0.00)	0.470 (0.01)	0.216 (0.00)	0.585 (0.00)	0.325 (0.00)	0.707 (0.02)
ADR_{t-1}	BSIR_{t-1}	EITI_{t-1}	VOLPREM_{t-1}	TURN_{t-1}	PE_{t-1}	TVR_{t-1}
0.531 (0.02)	0.304 (0.00)	0.351 (0.00)	0.146 (0.00)	0.688 (0.02)	0.265 (0.00)	0.639 (0.00)

Note: The values in parentheses are the p-value of the t statistics of the correlation coefficient.

The current values or lag values of the respective proxies are selected, whichever has a higher correlation with the provisional sentiment index (represented in bold in Table 1). Based on the correlation values, the selected proxies for constructing the final sentiment index are $EITI_t$, $VOLPREM_t$, PE_t , TVR_t , ADR_{t-1} , $BSIR_{t-1}$, $TURN_{t-1}$. Again, Principal Component Analysis is applied with the proxies mentioned above to obtain the final sentiment index.

Further, to ensure that the sample is fit for the application of principal component analysis, the KMO measure of sampling adequacy and Barlett's test of sphericity are estimated. The value of KMO is 0.630, and Barlett's test of sphericity has a significant level of 0.000, implying that the sample is adequate. The variance explained by the first principal component is 57%. The final sentiment index is represented as $SENT$.

$$SENT = 0.362EITI_t + 0.333VOLPREM_t + 0.230PE_t + 0.742TVR_t + 0.593ADR_{t-1} + 0.400BSIR_{t-1} + 0.799TURN_{t-1} \quad (8)$$

Four out of seven sentiment proxies, including equity issues to the total issues, volatility premium, price-to-earnings ratio, and turnover volatility ratio, have an immediate effect on investor sentiment. In contrast, the advance to decline ratio, buy-sell imbalance ratio, and share-turnover follow a lag of one month. Figure 1 shows the trend of the sentiment index.

The unit root tests were run to check the stationarity in the time series including the Augmented Dickey-Fuller Test (ADF) and the Phillips-Perron (PP) test. The results of PP and ADF tests are estimated, including with drift and no trend, along with drift and the trend. The lag length is selected using SIC (Schwarz Information Criterion) and AIC

Table 2. Results of unit root test, augmented Dickey-Fuller test, and Phillips-Perron test

Source: Authors.

Augmented Dickey-Fuller Test				
Variables	With Drift and no Time Trend		With Drift and Time Trend	
	Level	First Difference	Level	First Difference
BSE 500 Returns	-2.72**	-4.06**	-3.02**	-4.24**
SENT	4.34***	-4.25***	-5.65***	-6.98***

Phillips-Perron Test				
Variables	With Drift and no Time Trend		With Drift and Time Trend	
	Level	First Difference	Level	First Difference
BSE 500 Returns	-6.56***	-12.06***	-11.89***	-29.10***
SENT	-6.44***	-11.25***	-12.31***	-22.58***

Note: ** and *** show significance levels at 5% and 1%, respectively.

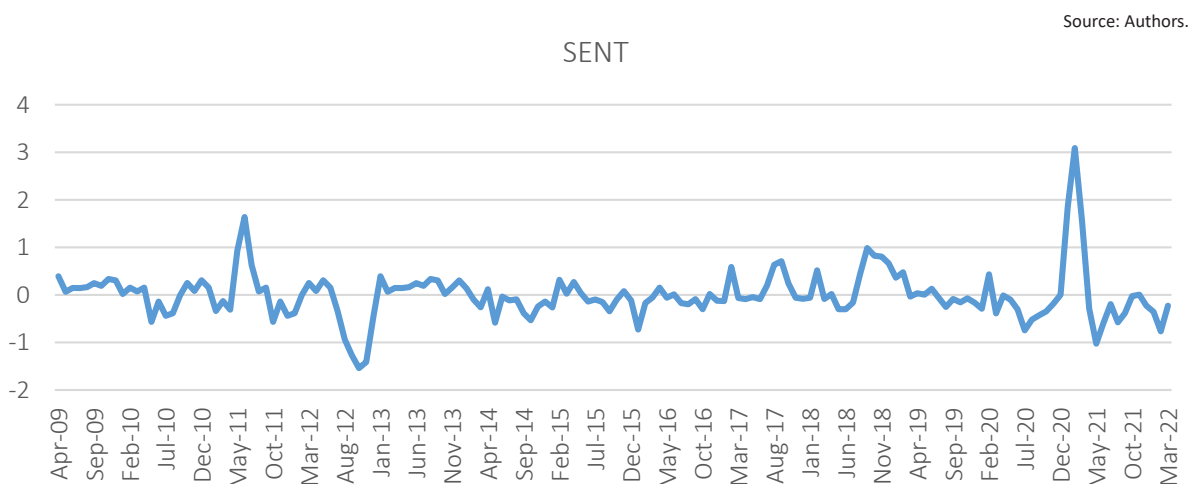


Figure 1. Sentiment index

(Akaike Information Criterion). The null hypotheses of unit root tests assume the presence of unit root, i.e., time-series variables are non-stationary. The results of the ADF and PP tests are shown in Table 2. The results of both PP and ADF tests, including that with drift and no trend and with drift and the trend at both levels and the first difference, reject the null hypotheses, indicating the series to be stationary and fit for further analysis.

3.2. Regression analysis

Table 3 shows the parameter estimates of regression analysis wherein the sentiment index is the predictor variable and market returns (proxied by BSE 500 returns) are the response variable. The F-statistic is reasonably high, indicating that the sentiment and its one-month lag contribute significantly to the returns' variance. In addition, the adjusted value of R^2 is 39%, which validates the model. Further, the Durbin-Watson statistic implies no existence of autocorrelation amongst resultant residuals (prediction error) at lag length 1, selected based on AIC and SIC criteria.

Table 3. Regression analysis results

Source: Authors.

Variable	Coefficient	S.E.	t-statistic
$SENT_t$	0.011	0.002	5.32**
$SENT_{t-1}$	-0.009	0.001	-11.58*
RM_{t-1}	0.298	0.037	7.96*
Adjusted R2 value	0.396		
F-statistic	22.9*		
Durbin-Watson Statistic	2.12 (p-value=0.02)		

Note: ** and *** show significance levels at 5% and 1%, respectively.

A significant positive relationship exists between market return and contemporaneous sentiment index, and a significant negative relationship exists with a one-month lagged value of investor sentiment and market returns. Further, there is a positive relationship between current market returns and one-month lagged values of market returns. Hence, past returns also play a significant role in driving current market returns. Figure 2 shows the trend of market returns and investor sentiment.

3.3. VAR analysis

The study employs VAR analysis using causality analysis, impulse response function, and variance decomposition analysis. To select the lag length for VAR analysis, this study uses various lag selection criteria (shown in Table 4), including the Likelihood-ratio Statistic (LR), Final Prediction Error (FPE), Akaike Information Criterion (AIC), Schwarz Information Criterion (SIC), and Hannan-Quinn Information Criterion (HQIC). All the criterion supports the selection of lag length one except for LR, which supports the selection of lag order 4. Further, the Wald test of exclusion is applied, starting with eight lags and moving backward. The results of the Wald test show the exclusion of lag 8, 7, 6, 5, and 3.

Hence, including the lag selection criterion and lag exclusion test results, the study uses lag 1, 2, and 4 in the final model. The estimated VAR model is represented as follows:

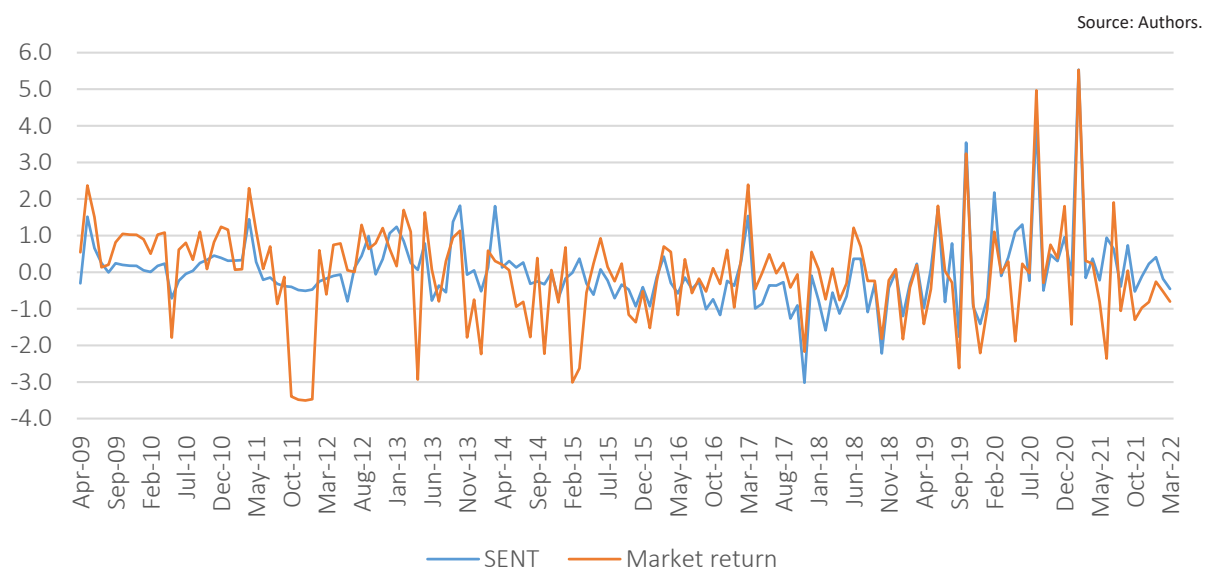


Figure 2. Trend of market returns and investor sentiment

Table 4. Lag length selection using various lag selection criteria

Source: Authors.

	LR	FPE	AIC	SIC	HQIC
0	NA	5.30501E-05	-4.335	-4.006	-4.089
1	23.916	7.43322E-14*	-11.63*	-10.613*	-10.946*
2	22.235	1.45E-16	-11.528	-10.726	-11.406
3	9.894	2.40078E-16	-11.536	-10.244	-11.376
4	7.286*	1.74017E-15	-12.235	-10.134	-11.012

$$RM_t = 0.00639SENT_{t-1} + 0.02456SENT_{t-2} - 0.00176SENT_{t-4} - 0.07821RM_{t-1} - 0.34612RM_{t-2} + 0.31602RM_{t-4} + 2.356, \quad (9)$$

$$SENT_t = 0.53462SENT_{t-1} + 0.45892SENT_{t-2} + 0.06052SENT_{t-4} - 46.218RM_{t-1} - 35.025RM_{t-2} + 27.265RM_{t-4} + 9.236. \quad (10)$$

Further, the study applies other statistical tools to interpret the VAR model’s parameter estimates.

3.3.1. Causality analysis

Table 5 presents the result of the Granger-Causality test between stock market returns and the sentiment index. The results show that in both cases, at a 5% significance level, both the null hypotheses are rejected, implying that stock market returns and SENT Granger cause each other, emphasizing that there exists bidirectional causality between market returns and SENT. However, the result of Granger causality from sentiment to returns is more marked than the result of Granger causality from returns to sentiment.

Table 5. Granger-causality test

Source: Authors.

Null Hypothesis	χ^2 statistic	Probability
RETURN does not Granger Cause SENT	19.622	0.00000
SENT does not Granger Cause RETURN	62.2989	0.00001

Further, to access contemporaneous causality, this study applies the Geweke (1982) procedure for which it computes various χ^2 statistics, as mentioned in Appendix A.

H_{01} : *RM does not lead SENT:*

$$n \cdot F_{RM \rightarrow SENT} = n \cdot \ln \left(\frac{T_1}{T_2} \right) = 12.57. \quad (11)$$

H_{02} : *SENT does not lead RM:*

$$n \cdot F_{SENT \rightarrow RM} = n \cdot \ln \left(\frac{\Sigma_1}{\Sigma_2} \right) = 34.96. \quad (12)$$

H_{03} : *No instantaneous relationship between RM and SENT:*

$$n \cdot F_{RM \cdot SENT} = n \cdot \ln \left(\frac{T_2}{T_3} \right) = 57.43. \quad (13)$$

H_{04} : *No instantaneous or lagged relationship between RM and SENT:*

$$n \cdot F_{RM \cdot SENT} = n \cdot \ln \Sigma_1 \left(\frac{T_1}{|Y|} \right) = 98.64. \quad (14)$$

All the above null hypotheses are rejected as the critical chi-square value at 1 degree of freedom and at 5% probability is 3.84, and all the values are much greater than the critical value. This provides strong evidence that both sentiment and market return affect each other instantaneously. Also, the Granger causality results show a bidirectional relationship between sentiment and market return with a time lag. Hence, the sentiment-return bidirectional relationship exists in the Indian market for both contemporaneous and lagged effects.

3.3.2. Impulse response analysis

As all variables in a VAR model are interdependent, the impulse response analysis describes the changes in the variables of a VAR model in response to a shock in one or more variables. The SVAR (Structural vector autoregression) model is used to extract cultural shocks for which the study follows Cholesky ordering. This study illustrates four impulse response functions with 12-period lags, illustrating the effect of market returns and investor sentiment on one another over 12 months time frame. Four impulse response analyses are depicted in Figure 3.

The graph representing “Response of SENT to SENT” (see Figure 3) shows the impulse response of senti-

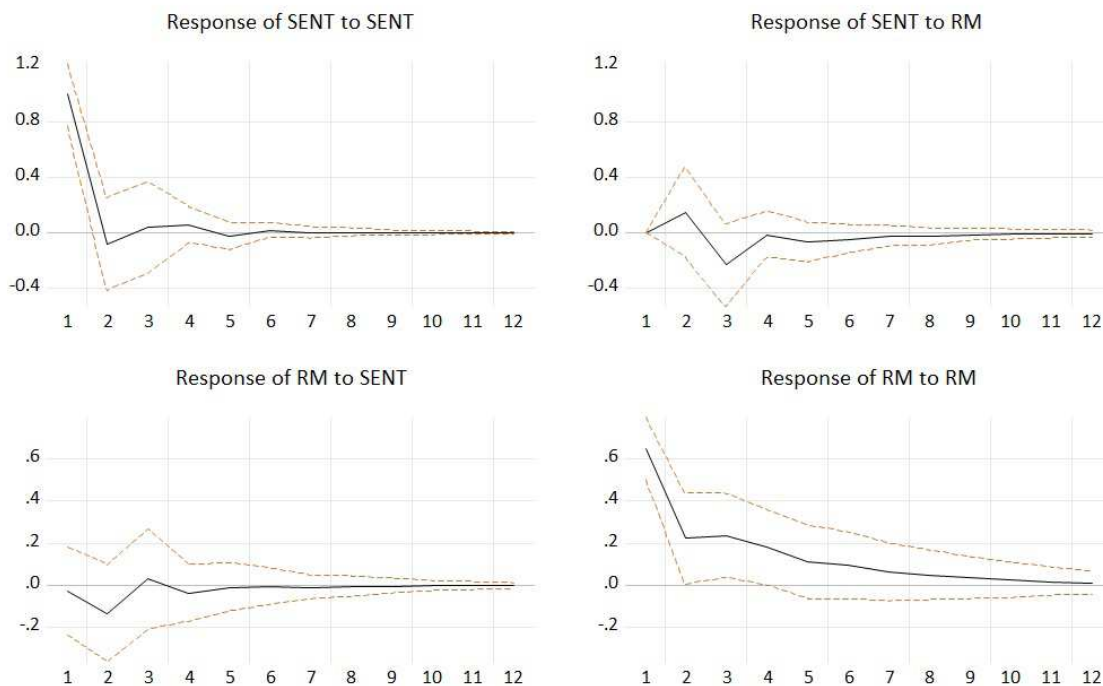


Figure 3. VAR-Impulse response analysis

ment due to shocks in sentiment itself. The resultant impact is positive up to the first eight lags but moves downwards and becomes insignificant over further lags. This supports that lagged sentiment has a significant impact on the current sentiment.

The graph representing “Response of SENT to RM” (see Figure 3) shows sentiment response due to shocks originating in market returns. The shock response of sentiment is positive for nine lags but shows a downward trend with minor corrections but becomes insignificant over further lags confirming the fact that past market returns significantly influence the sentiment of the investors, but the impact of returns on sentiment fades with time.

The graph representing “Response of RM to SENT” (see Figure 3) shows how market returns react due to shocks in investor sentiment. The response of market return, although it shows a downward trend over the time lags, is positive across all the lags but starts to fade away (becomes insignificant) from lag 10. This confirms that investor sentiment strongly affects market returns, and the effect is pronounced over several months.

The “Response of RM to RM” graph (see Figure 3) shows how market returns react to the shocks

originating from market returns itself. It highlights that the response of market return is positive but shows decreasing trend due to shocks in the market return itself. This interpretation is in line with the regression results (in section 4.2), wherein past market returns positively affect current market returns.

3.3.3. Variance decomposition analysis

Variance Decomposition Analysis shows the amount of information that each variable contributes to the other variables in the VAR model. Table 6 shows the percentage of variation that returns and sentiment explain owing to shocks in return and sentiment. This study shows the results of variance decomposition spread over 12 months’ time-period. The results of variance decomposition of sentiment show that sentiment shocks account for 38.07% variation in market returns and 61.93% of the variance in sentiment initially, which decreases to 16.23% for market returns and increases to 83.77% for sentiment over 12 months. Also, the return shocks lead to 99.99% variation in the return and 0.01% variation in the sentiment in the first month, which decreases to 91.24% for market return and increases to 8.76% for the sentiment.

Table 6. Variance decomposition analysis

Source: Authors.

Period	Variance Decomposition of Sentiment		Variance Decomposition of Return	
	RM	SENT	RM	SENT
1	38.07	61.93	99.99	0.01
2	32.56	67.44	99.97	0.03
3	29.43	70.57	97.34	2.66
4	25.69	74.31	96.22	3.78
5	21.9	78.1	96.16	3.84
6	19.28	80.72	95.52	4.48
7	18.82	81.18	93.32	6.68
8	18.67	81.33	92.51	7.49
9	17.98	82.02	92.45	7.55
10	17.72	82.28	92.27	7.73
11	17.29	82.71	91.32	8.68
12	16.23	83.77	91.24	8.76

4. DISCUSSION

Consistent with the findings of previous studies in the Indian context (Aggarwal & Mohanty, 2018; Chakraborty & Subramaniam, 2020; Dash & Mahakud, 2012, 2013; Dash & Maitra, 2018; Pandey & Sehgal, 2019), this study documents that investor sentiment strongly affects stock market returns. The results of the regression analysis highlight that the adjusted R^2 value is fairly high (almost 40%), supporting the fact that investor sentiment affects stock market returns and can explain the variation in stock market returns.

Moreover, the majority of the literature shows a well-documented negative sentiment-return relationship (Baker & Wurgler, 2006; 2007; McGurk et al., 2020; Rashid et al., 2019; Schmeling, 2009; Yu & Yuan, 2011; Yu et al., 2014), but this study documents the existence of a positive relationship between investor sentiment and stock concurrent market returns which is in line with the findings of Aggarwal and Mohanty (2018), Ryu et al. (2017), Xu and Zhou (2018), and Verma and Verma (2007). The estimated coefficient values indicate that a one percent increase in contemporaneous investor sentiment results in an eleven percent increase in the current market returns. The positive correlation between investor sentiment and stock market returns could be due to domination of institutional investors in the Indian market or due to the trading behavior of Indian investors.

Further, a significant negative relationship exists between a one-month lagged investor sentiment and current market returns. This cause could be attributed to a higher number of speculative investors in the Indian market. A one percent decrease in the lagged sentiment results in a decrease of nine percent in the market return after one month, which shows that the large portion of the sentiment effect on the market return is eliminated after one month. Moreover, past returns also play a significant role in driving current market returns, as a one percent increase in the one-month lag returns leads to a 30% increase in the current market returns. The findings of the study are consistent with those of Anusakumar et al. (2017) and Khan and Ahmad (2018), highlighting the high degree of presence of irrational investors in the Indian market who tend to trade on incomplete information indicating noise in the market, leading to overvaluation (undervaluation) of stock returns.

Moreover, the results of variance decomposition analysis show that shocks in returns and sentiment explain a large percentage of variation in sentiment and returns, respectively. The results are consistent with the study of Khan and Ahmad (2018), Li (2021), and Yu et al. (2014), as they advocate that sentiment-driven excess return is more prominent in the short run but optimizes in the long run, but the effect of sentiment on returns is more pronounced than that of returns on the sentiment which contradicts the findings of Khan and Ahmad (2018).

This study employs the Geweke and Granger-causality tests to study contemporaneous and lagged bidirectionality, respectively, between sentiment and returns. The results of causality tests emphasize that there exists a contemporaneous as well as lagged bidirectional causal relationship between investor sentiment and stock market returns. The existence of causal bidirectionality at lag is inconsistent with the findings of Dash and Mahakud (2013) and Dash and Maitra (2018), who document that primarily returns do not Granger cause investor sentiment. The findings of this study are consistent with that of Khan and Ahmad (2018), Sehgal et al. (2010), and Schmeling et al. (2009), who support the existence of lagged bidirectional sentiment-return relationship. Further, Naik and Padhi (2016) found that the bidirectional sentiment-return relationship exists at the third

lag. The possibility behind the difference in the findings might be attributed to the difference in the proxies selected for measuring sentiment.

Further, this study also documents the existence of contemporaneous bidirectionality between return and sentiment in line with the study of Khan and Ahmad (2018), which has been ignored in most

studies that study sentiment-return bi-directionality. Future researchers in the area can study the contemporaneous sentiment-return bidirectional relationship in their respective markets. They can also study sentiment-return bi-directionality in the short and long run using ARDL (autoregressive distributed lag model) and VECM (vector error correction model) approaches.

CONCLUSION

The study's objective was to assess the effect of investor sentiment on the stock market returns and to evaluate the bidirectional relationship between investor sentiment and stock returns for the Indian market from April 2009 to March 2022. The results of bidirectionality tests are inferred using causality analysis, impulse response function, and variance decomposition analysis.

The results show that current market returns have a positive relationship with current sentiment and lagged market returns. Hence, it can be inferred that not only sentiment but past returns also influence current market returns. Further, the study documents a negative relationship between lagged sentiment and current market returns. Furthermore, the results of causality tests, including Granger-causality (lagged response) and Geweke-causality (instantaneous feedback), confirmed the presence of a bi-directional relationship between sentiment and returns for the current and lagged time period, respectively. Furthermore, the impulse response analysis between sentiment and return indicates that sentiment strongly affects market returns as the impact of sentiment

on returns is pronounced for contemporaneous and lagged time-period, with the sentiment effect lasting for over six months, after which the market corrects itself over subsequent months. Further, the variance decomposition analysis results also support the two-way response between sentiment and returns, but the shocks emanating from sentiment on market returns is more than the effect of shocks emanating from market returns on sentiment.

The contribution of this study is manifold. Firstly, this study is the first to explore the contemporaneous bidirectional causality between investor sentiment and stock returns in the Indian context. Secondly, this study highlights the role of past returns in influencing current market returns. Further, the research is significant for academicians and traders as India is a developing economy that offers limited arbitrage opportunities wherein a large number of retail investors trade on noise. Hence, policymakers should develop trading strategies keeping in mind the bilateral sentiment-return relationship to avoid frequent market bubbles or crashes.

AUTHOR CONTRIBUTIONS

Conceptualization: Ajit Yadav, Vijaya.

Data curation: Ajit Yadav.

Formal analysis: Ajit Yadav, Vijaya.

Investigation: Ajit Yadav.

Methodology: Ajit Yadav, Vijaya.

Project administration: Ajit Yadav, Anindita Chakraborty.

Software: Anindita Chakraborty.

Supervision: Anindita Chakraborty.

Validation: Vijaya.

Visualization: Vijaya.

Writing – original draft: Ajit Yadav.

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APPENDIX A

Appendix A shows Geweke's approach in detail.

According to Geweke (1982), "the measure of linear dependence is the sum of the measures of the three types of linear feedback, $F_{X,Y} = F_{X \rightarrow Y} + F_{Y \rightarrow X} + F_{X,Y}$ ". Considering two zero mean time series RM and SENT, the six equations of Geweke's test are shown below:

$$RM_t = \sum_{i=1}^p a_{1i} RM_{t-i} + \mu_{1t}, \quad (A1)$$

$$SENT_t = \sum_{i=1}^p b_{1i} SENT_{t-i} + \nu_{1t}, \quad (A2)$$

$$RM_t = \sum_{i=1}^p a_{2i} RM_{t-i} + \sum_{i=1}^p c_{2i} SENT_{t-i} + \mu_{2t}, \quad (A3)$$

$$SENT_t = \sum_{i=1}^p b_{2i} SENT_{t-i} + \sum_{i=1}^p d_{2i} RM_{t-i} + \nu_{2t}, \quad (A4)$$

$$RM_t = \sum_{i=1}^p a_{3i} RM_{t-i} + \sum_{i=0}^p c_{3i} SENT_{t-i} + \mu_{3t}, \quad (A5)$$

$$SENT_t = \sum_{i=1}^p b_{3i} SENT_{t-i} + \sum_{i=0}^p d_{3i} RM_{t-i} + \nu_{3t}, \quad (A6)$$

where a_{1i} , b_{1i} , a_{2i} , b_{2i} , c_{2i} , d_{2i} , a_{3i} , b_{3i} , c_{3i} , and d_{3i} are the coefficients of the auto-regressive model and μ_{1t} , ν_{1t} , μ_{2t} , ν_{2t} , μ_{3t} , and ν_{3t} are the residuals with mean equal to zero.

Further, $\text{var}(\mu_{1t}) = \Sigma_1$, $\text{var}(\nu_{1t}) = T_1$, $\text{var}(\mu_{2t}) = \Sigma_2$, $\text{var}(\nu_{2t}) = T_2$, $\text{var}(\mu_{3t}) = \Sigma_3$, $\text{var}(\nu_{3t}) = T_3$. The variances Σ_1 , T_1 , Σ_2 , T_2 , Σ_3 , and T_3 are estimated using OLS regression.

The measure of linear feedback of the Geweke procedure is shown below:

$H0_1$: RM does not lead SENT:

$$n \cdot F_{RM \rightarrow SENT} = n \cdot \ln \left(\frac{T_1}{T_2} \right) \sim \chi_p^2.$$

$H0_2$: SENT does not lead RM:

$$n \cdot F_{SENT \rightarrow RM} = n \cdot \ln \left(\frac{\Sigma_1}{\Sigma_2} \right) \sim \chi_p^2,$$

where $F_{SENT \rightarrow RM}$ shows the propensity of the time-series SENT Granger-causing RM, and $F_{RM \rightarrow SENT}$ specifies the propensity of time series RM Granger-causing SENT. The measure of instantaneous linear feedback is calculated as:

$H0_3$: No instantaneous relationship between RM and SENT:

$$n \cdot F_{RM \cdot SENT} = n \cdot \ln \left(\frac{T_2}{T_3} \right) \sim \chi_1^2.$$

H_{0_i} : No instantaneous or lagged relationship between RM and SENT:

$$n \cdot F_{RM-SENT} = n \cdot \ln \Sigma_1 \left(\frac{T_1}{|Y|} \right) \sim \chi^2_{(2p+1)},$$

where Y is the covariance matrix, C is the covariance of two error terms μ_{2t} and v_{2t} .

$$Y = \text{var} \begin{pmatrix} \mu_{2t} \\ v_{2t} \end{pmatrix} = \begin{bmatrix} \Sigma_2 & C \\ C & T_2 \end{bmatrix}.$$

APPENDIX B

Appendix B shows the details of the sentiment proxies selected for the study, including their meaning and significance.

Table B1. The sentiment proxies for measuring investor sentiment

Source: Authors.

Advance to decline ratio (ADR)	The ratio between the stocks with higher closing prices than the previous day to that of stocks with lower closing prices than the previous day.	ADR>1 Bullish sentiment ADR<1 Bearish sentiment ADR = 1 No trend
Price to Earnings ratio (PE.)	The ratio between the firm's market price and earnings per share.	PE high- Overvaluation PE low-Undervaluation
Share Turnover (TURN)	The ratio between the number of shares traded and the outstanding shares of a firm.	TURN increases- Bullish Sentiment TURN decreases- Bearish sentiment
Volatility Premium (VOLPREM)	The price-to-book ratio of high volatile stocks to that of low volatile stocks. Volatility is measured as the standard deviation in the stock returns.	VOLPREM>1- High return stability VOLPREM<1- Low return stability
Buy-Sell Imbalance Ratio (BSIR)	The ratio of the buy orders minus the sell orders divided by the total buy plus sell orders.	BSIR>0 Bullish sentiment BSIR<0 Bearish sentiment
Equity issuance in total issuance (EITI)	The ratio of the equity issues to the total issues (equity issues + debt issues).	EITI high- Bullish sentiment EITI low- Bearish sentiment
Turnover Volatility Ratio (TVR)	The ratio of market turnover (Trading volume/ Market capitalization) to the standard deviation of stock market returns	TVR high- Bullish sentiment TVR low- Bearish sentiment

APPENDIX C

Appendix C shows the descriptive statistics of the sentiment proxies and their inter-item correlations.

Table C1. Descriptive statistics of the sentiment proxies

Source: Authors.

Descriptive statistics of the standardized sentiment proxies									
	N	Min	Max	Mean	Standard Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
ADR	156	-2.2211	4.9851	0.0000	0.9115	0.9186	0.194	3.205	0.401
BSIR	156	-3.6684	5.8865	0.0000	0.9103	1.5226	0.194	8.684	0.401
EITI	156	-3.5760	1.4105	0.0000	1.0000	-1.5753	0.194	2.022	0.401
VOLPREM	156	-2.8034	5.1652	0.0000	0.7170	1.9324	0.194	16.739	0.401
TURN	156	-1.4814	9.5615	0.0000	0.6723	6.1423	0.194	2.868	0.401
PE	156	-1.8413	5.6083	0.0000	0.8005	2.9028	0.194	22.706	0.401
TVR	156	-1.7512	5.1645	0.0000	0.8368	1.9738	0.194	30.192	0.401

Inter-correlation between standardized sentiment proxies							
	ADR	BSIR	EITI	VOLPREM	TURN	PE	TVR
ADR	1						
BSIR	-0.155*	1					
EITI	-0.088*	-0.160**	1				
VOLPREM	-0.218**	-0.068	-0.143*	1			
TURN	0.067*	0.044	-0.019*	0.160*	1		
PE	0.090*	-0.041*	-0.062*	0.090	0.100*	1	
TVR	-0.179*	0.035**	0.242*	0.130**	0.134*	-0.421*	1

Note: * and ** show significance at 1% and 5% levels, respectively.