Research Article

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Economic Sentiment and Market Return of Indian Stock Market: An ARDL Approach

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Abstract

This study investigates the relationship between economic sentiment and the return of the BSE S&P 500 Index over a decade, employing an autoregressive distributed lag (ARDL) model. Using 12 macroeconomic variables as proxies for economic sentiment, the analysis reveals a high degree of correlation between these proxies and market return. The findings demonstrate that market return is significantly influenced by its own lags, economic corporate premium (ECORPREM), foreign direct investment (FDI), gross domestic product (GDP), inflation rate (INFLAT), prime lending rate (PLR), and short-term interest rate (SHORTINT). Specifically, market return shows both positive and negative correlations with its various lags, while ECORPREM, FDI, GDP, and SHORTINT exhibit significant relationships with market return at different lag intervals. Additionally, INFLAT positively influences market return at specific lags, and PLR is positively correlated with market return in the current period.

The study identifies that ECORPREM, FDI, GDP, INFLAT, PLR, and SHORTINT, with p-values below 0.20, are statistically relevant in explaining market return. Conversely, variables such as exchange rate (EXRATE), foreign exchange reserves (FEXRES), index of industrial production (IIP), liquidity in the economy (LIQECO), oil prices (OILPRICE), and terms of trade premium (TERMSPRE) do not significantly impact market return, as indicated by their higher p-values. These results provide valuable insights for retail investors, policymakers, and other stakeholders in refining their decision-making processes in the Indian stock market. The study also challenges the classical finance theory of investor rationality, suggesting avenues for further research in international contexts.

Keywords: Behavioral finance. Economic sentiment. Macroeconomic variables. Multivariate regression. Principal component analysis. Stock market return.

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1 Introduction

Behavioral finance is a branch of finance that aims to predict market movements by understanding investor sentiments. Kahn's (2022) was the first to introduce the term "investor sentiment," highlighting that sentiment significantly influences economic activities. He emphasized that investors possess "animal spirits," which drive their investment decisions.

Gal's (1998) reported that behavioral economists believe investors undervalue public information while overvaluing private information. Consequently, investors with access to private

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information may achieve superior returns. As the number of companies and investors grows, financial access is no longer restricted to a select few.

As stock markets become more populated, systematic patterns in investor behavior have been observed (Mittal2017; Kumar & Lee, 2006). Traditional theories and models struggle to explain the impact of investor behavior on the stock market, leading to anomalies and market movements that are difficult to interpret.

Investors use various tools and techniques to analyze and predict stock market movements, considering factors such as share price patterns, historical financial performance, financial ratios, and accounting ratios. However, these methods often overlook the impact of human behavior on market movements and returns. Petty's (2012) defined attitude as a learned tendency to respond consistently in a favorable or unfavorable manner toward a particular object.

Behavioral finance suggests that investors behave emotionally in financial markets, with this emotional behavior termed sentiment. Various factors, including noise, influence investors' emotions, leading to unexpected buying and selling and sometimes causing market rallies or snowball effects. To understand how the economy functions, is managed, and grows, it is essential to comprehend investors' decision-making patterns and the reflections of their thoughts, moods, and animal spirits in financial markets. Numerous studies in the Western world have measured investor sentiment to predict market returns and volatility. However, such studies are still in their infancy in India. While these studies address measuring investor sentiment and its relationship with market returns, no study has focused on measuring economic sentiment and its correlation with market returns.

Researchers like Domian and Reiehenstein's (1998), Sehgal, Sood, and Rajput's (2010), Ray's (2012a), Hassan, Rashid, and Castro's (2016). Naik and Padhi's (2016), and Kumari and Mahakud's (2016) have used macroeconomic factors as proxies for investor sentiment, combining them with other proxies to predict market returns. It remains to be seen whether market returns can be predicted using macroeconomic factors alone, assuming these factors represent economic sentiment. To our knowledge, no study has yet attempted to predict market returns solely based on macroeconomic factors representing economic sentiment.

This study is divided into six sections. The second section reviews the literature, the third outlines objectives and hypotheses, the fourth discusses research methodology, the fifth presents results and data analysis, and the sixth concludes the study.

2 Review of Literature

In the world of economics, Kahn's (2022) pioneered the idea that sentiment plays a crucial role in economic activities. This groundbreaking concept laid the foundation for future scholars to delve deeper into the intricate relationship between sentiment and the economy.

Years later, a group of researchers led by Shanken and Weinstein's (2006) embarked on a quest to uncover the influence of macroeconomic factors on stock market changes. They discovered that elements such as long-term government bonds, industrial production, oil prices, and inflation could sway market movements. Their findings revealed a connection between non-economic variables and market returns, highlighting additional macroeconomic factors that play a role.

Fisher and Statman's (2000) an turned their attention to the sentiments of different investor groups—large, medium, and small. They unearthed a strong bond between individual investors' sentiment and that of newsletter writers, but Wall Street strategists remained unaffected. Despite sentiment alone not predicting market returns, they found that the combined sentiment from all groups held the power to do so, pointing towards the significance of implied sentiment indicators.

Venturing further, Kumar and Lee's (2006) employed the GARCH-in-mean approach to investigate how investor sentiment impacts the relationship between market returns and volatility.

Using the investors' intelligence index as a proxy, they observed a fascinating trend: volatility surged when investors were bearish and declined when they were bullish, illustrating a negative relationship between volatility and sentiment.

Baker and Wurgler's (2004a, 2004b) then hypothesized that sentiment could be measured through selected proxies to predict market trends. They developed a sentiment index, concluding that stocks yielded higher returns during low sentiment periods and lower returns during high sentiment times. Their research also suggested an increased likelihood of market crashes following high sentiment periods.

Verma, Baklaci, and Soydemir's (2008) noted that investor sentiment comprised both rational and irrational elements, impacting the Market Price of Risk (MPR). They discovered that irrational sentiment had a negative correlation with MPR and the rational sentiment of arbitrageurs, particularly for the DJIA and S&P500. While irrational optimism heightened market volatility, rational investor sentiment seemed to have no significant effect on MPR, with rational investors often adopting bearish stances when noise traders were bullish, and vice versa.

Sehgal, Sood, and Rajput's (2009) took a different approach, conducting a survey to define investor sentiment. The majority of respondents perceived sentiment as the understanding of human behavior influencing market returns. Kuzmina (2010) further categorized investors into rational, noise, and emotional types, concluding that while emotional investors might enjoy short-term gains, their wealth aligned with rational investors in the long run.

In the Indian context, Sehgal, Sood, and Rajput's (2010) utilized Baker and Wurgler's (2006) methodology to construct a sentiment index, demonstrating its predictive power for the market, albeit with challenges in establishing a cause-and-effect relationship. Bennet (2011a, 2011b) also focused on the Indian stock market, exploring the interplay between market-specific factors and investor sentiment, optimism, and outlook.

Dash and Mahakud's (2013a) and Dash and Mahakud's (2013b)analyzed sentiment's impact on industrial returns, suggesting that fund managers should favor stocks from less sentiment-sensitive industries. Meanwhile, Bu and Pi's (2014) reported that both fundamentalist and noise trader sentiments influence prices, constructing an investor sentiment index for the Chinese stock market that proved predictive for the CSI300 index.

Kumari and Mahakud's (2015) delved into the relationship between investor sentiment, stock market return, and volatility, validating the noise trader theory and affirming sentiment's predictive capabilities. Naik and Padhi's (2016) used Baker and Wurgler's (2006) methodology to create positive and negative sentiment indices, establishing a bi-directional causality between sentiment and market returns.

He, Zhu, and Gu's (2017) challenged the efficient market hypothesis, highlighting the limitations of classical finance theory in explaining abnormal stock price changes. They created a provisional investor sentiment index for China's stock market, using the GARCH model to demonstrate a feedback loop between sentiment and the stock index.

Finally, Pandey and Sehgal's (2019), employing Baker and Wurgler's (2006) methodology, constructed various sentiment indices to underscore sentiment's significance in the stock market. They concluded that the FF3f and FF5f models offered superior asset pricing capabilities when incorporating sentiment factors. And thus, the story of investor sentiment and its profound impact on the stock market continues to evolve, driven by the relentless pursuit of knowledge by economists and researchers alike.

Given the extensive body of research demonstrating the significant influence of sentiment on market returns, this study aims to further explore the nuanced relationship between economic sentiment and market performance. By analyzing how sentiment affects market returns, especially in the context of evolving economic conditions, this study seeks to provide deeper insights that could enhance predictive models and inform investment strategies. Additionally, this research will investigate the role of various macroeconomic variables, recognizing that not all such factors significantly impact market returns, thereby providing a comprehensive understanding of both impactful and non-impactful variables in the sentiment-market return dynamic. This research will contribute to the existing literature by offering a contemporary analysis, addressing gaps, and potentially uncovering new patterns in the sentiment-market return dynamic.

3 Objectives and Hypotheses of Study

3.1 Research Objectives

1. To identify the proxies to the economic sentiment.
2. To analyze the relationship between economic sentiment and market return over long-run.
3. To identify the significant economic sentiment proxies to predict market return over long-run.
4. To suggest the policy implications.

3.2 Research Hypotheses

Whether there is any relationship between economic sentiment and market return, to know this, we set the following hypotheses:

H0: There is no significant relationship between economic sentiment and market return.

H1: There is a significant relationship between economic sentiment and market return.

These hypotheses serve as the cornerstone of our investigation into the potential linkages between market return and sentiment sub-indices. Through rigorous analysis and empirical testing, we aim to either accept or refute these hypotheses, thereby illuminating the existence and nature of any long-term associations between market performance and sentiment indicators. This systematic approach ensures that our findings contribute significantly to the understanding of how sentiment influences market dynamics over time.

3.3 Rationale of the Study

The impact of economic sentiment on market return can be assessed using similar principles and methodologies employed in the analysis of investor sentiment. Both investor and economic sentiments are critical drivers of market behavior, reflecting collective perceptions and expectations that influence financial decisions. Just as investor sentiment, measured through proxies like trading volume or surveys, affects market returns through psychological and behavioral mechanisms, economic sentiment, gauged through macroeconomic indicators (or surveys also), impacts market performance by shaping expectations about future economic conditions.

These studies collectively provide a robust empirical foundation for understanding the impact of both investor and economic sentiment on market returns. So, empirical evidence supports the significant role of both types of sentiment in financial markets. Numerous studies Baker and Wurgler's (2004a, 2004b, 2006) have established the correlation between investor sentiment and market returns, highlighting the importance of perceptions and behavioral biases in driving market dynamics. Similarly, economic sentiment influences market returns by affecting corporate earnings, investment decisions, and overall economic outlook. Ludvigson's (2004) examines the link between consumer confidence (a proxy for economic sentiment) and consumer spending, indicating that higher confidence levels predict increased spending, which in turn influences market returns. Carroll, Fuhrer, and Wilcox's (1994) investigates whether consumer sentiment indexes forecast household spending and subsequently affect stock market performance, finding a significant predictive relationship. Howrey's (2001) explores the predictive power of the Index of Consumer Sentiment for economic activity and market returns, demonstrating its effectiveness as a leading indicator.

3.4 Methods for Analysis

By employing robust econometric models like the ARDL framework, we can effectively capture the relationship between economic sentiment and market return, drawing parallels with the well-documented impact of investor sentiment. This approach not only enhances our understanding of market behavior but also provides valuable insights for investors and policymakers in formulating strategies to navigate market fluctuations.

4 Research Methodology

4.1 Selection of Macroeconomic Factors

The twelve factors included in the regression equation have been identified based on a review of existing literature. These factors are as follows:

- Foreign Direct Investment (FDI): FDI refers to investments made by investors from one country in another country. This can involve acquiring a foreign business, establishing a new business abroad, or acquiring assets of an established business in another country. An increase in FDI suggests that foreign investors perceive potential in the host country, generally indicating positive economic prospects. An increase in FDI can positively affect investor sentiment and market returns, while a decrease may have the opposite effect (Hassan, Rashid, & Castro, 2016; Raza et al., 2012). Haq's (2019) also reported a positive relationship between FDI and stock market returns.
- Economic Risk Premium (R_m-R_f) (ECORPREM): The economic risk premium is the difference between market return and the risk-free rate of return. In this study, the return on S&P BSE 500 is used as a proxy for market return, and the interest rate on 364-day T-Bills represents the risk-free rate. The difference between these two rates is considered the economic risk premium.
- Oil Prices (OILPRICE): Oil prices play a significant role in the global economy. While some research suggests that investor sentiment may influence oil prices, there is limited experimental evidence. Literature indicates that oil prices primarily impact the stock prices of oil companies and those using oil-based raw materials (Du, Gunderson, & Zhao, 2016). An increase in oil prices is generally expected to lead to a market downturn and vice versa.
- Liquidity in the Economy (LIQECO): Liquidity in the economy can be measured by the monetary base or high-powered money, denoted by M1, which includes currency with the public, cash reserves of commercial banks, and other deposits with the central bank (RBI in India). This study considers liquidity as a proxy for investor sentiment, consistent with Sehgal, Sood, and Rajput's (2010).
- Inflation (INFLAT): Inflation, the reduction in purchasing power of money, is measured using the Wholesale Price Index (WPI) and Consumer Price Index (CPI). Inflation can negatively impact investor sentiment and market returns (Kumari & Mahakud, 2016; Naik & Padhi, 2016; Sehgal, Sood, & Rajput, 2010). This study uses the percentage change in WPI, incorporating a two-month lag to account for reporting delays (Huang et al., 2015).
- Level of Interest Rate (PLR): The Prime Lending Rate (PLR) is the interest rate at which banks lend to their most creditworthy customers and serves as the base for other interest rates.

Changes in PLR affect the money supply and market dynamics. A decrease in PLR can boost market activity and positively influence sentiment, while an increase can have the opposite effect.

- Term Spread (TERMSPRE): Term spread is the difference between long-term and short-term interest rates, measured here as the difference between 364-day and 91-day T-Bills. A positive term spread typically indicates higher long-term interest rates compared to short-term rates and can negatively affect sentiment (Domian & Reiehenstein, 1998; Naik & Padhi, 2016).
- Index of Industrial Production (IIP): The IIP measures the monthly growth rate of industrial production in a country, reflecting economic growth. An increase in IIP indicates economic growth, positively impacting investor sentiment and market returns. This study uses the general IIP with a base year of 2011-12, adjusted for lagged data to account for reporting delays (Huang et al., 2015).
- Short-term Interest Rate (SHORTINT): The short-term deposit interest rate is the rate on deposits made for less than one year. Changes in this rate can influence investor decisions to move money between banks and the stock market. An increase in short-term rates may negatively impact sentiment, while a decrease can have a positive effect.
- Exchange Rate (EXRATE): The exchange rate is the value of one currency relative to another. Fluctuations in exchange rates can impact the financial position of companies. A weaker rupee may hurt Indian importers but benefit exporters, impacting investor sentiment (Nair, 2018). This study uses the exchange rate of the Indian rupee to the US dollar.
- Foreign Exchange Reserves (FEXRES): Foreign exchange reserves, held by the RBI in foreign currencies, provide a cushion in emergencies and strengthen the rupee. Higher reserves positively impact the stock market and investor sentiment (Ray, 2012a, 2012b).
- Gross Domestic Product (GDP): GDP represents the monetary value of all final goods and services produced in an economy over a period. Growth in GDP positively affects investor sentiment and market returns (Kishorsinh, Chavda, & Kumar, 2018). This study uses quarterly GDP data, converted to a monthly series using temporal disaggregation and the Chow-Lin method (Chow & Lin, 1971).

These factors are assumed to represent the economic sentiment of the market. The codes used for each factor are provided in parentheses.

4.2 Data and Methodology

The research utilized a dataset comprising 141 monthly observations spanning from April 2010 to December 2021. This dataset included 12 proxies for economic sentiment, sourced from various platforms such as the BSE, NSE, RBI, SEBI, indexmundi.com, IMF, CSO, and the Department for Promotion of Industry and Internal Trade (see table 1). These 12 proxies have been discussed earlier in this section.

The data underwent rigorous refinement and standardization procedures. Unit root tests (ADF and PP) were employed to ensure stationarity. First-order differencing was then applied to render the series stationary. The BSE500 was chosen as the market benchmark for this study due to its comprehensive representation of 500 reputable Indian companies listed on the Bombay Stock Exchange.

Drawing from the methodological framework introduced by Pesaran and Shin's (1996), we employed the Auto-Regressive Distributed Lag (ARDL) approach to investigate the long-term relationship between market return and sentiment sub-indices in the Indian stock market. This analytical methodology aligns with the framework proposed by Tripathi and Kumar's (2015a, 2015b) , providing a robust foundation for our research.

Utilizing Eviews 12 software, we applied the ARDL model to determine the optimal lag length,

Table 1. Sources of Data for the Macroeconomic Factors

Sr. No.	Variable	Description	Source
1	FDI	"Foreign direct investment ( )"	Department for Promotion of Industry and Internal Trade website
2	ECORPREM	"Difference between market return and risk-free rate of return"	BSE website, RBI website
3	OILPRICE	"Oil prices ( )"	indexmundi.com
4	LIQECO	"Liquidity in the economy as measured through M3 ( )"	RBI website
5	INFLAT	"Inflation in the economy as measured through WPI"	RBI website
6	PLR	"Level of interest rate as measured through prime lending rate"	IMF website
7	TERMSPRE	"Term spread measured as difference between 364 days treasury bills and 91 days treasury bills"	RBI website
8	IPI	"Level of industrial production as measured through industrial production index"	RBI website
9	SHORTINT	"Short-term interest rate as measured through Short-term deposit interest rate"	RBI website
10	EXRATE	"Exchange rate of the Indian rupee ( ) to US dollar (\$)"	OFX website (previously known as OzForex)
11	FEXRES	"Foreign exchange reserves of India ( )"	RBI website
12	GDP	"Gross domestic product"	CSO and RBI website

Source: (Rohilla & Tripathi, 2022)

facilitating a comprehensive analysis. This approach allows us to explore the intricate dynamics between market return and sentiment sub-indices. By employing this methodology, we aim to uncover the underlying mechanisms governing market behavior, offering valuable insights into the interplay between economic sentiment variables and market returns over time. An auto-regressive distributed lag model is defined as follows:

$$Y_t = \alpha + \sum_{i=1}^{p} \beta_i Y_{t-1} + \sum_{j=0}^{q} \delta_j X_{t-j} + \epsilon_t \tag{1}$$

Where,

- Y_t = Market return (Stationary variable)
- X_{t-j} = Lagged values of economic sentiment proxies (Stationary variables)
- β_i and δ_j = Coefficients to be estimated
- ϵ_t = Error term

Ensuring the stationarity of our data is imperative for the robustness of our econometric analysis, particularly for employing advanced techniques like the ARDL model (Tripathi & Kumar, 2015a, 2015b). Stationarity implies that the mean, variance, and auto-covariance of a time series remain constant over time. To confirm stationarity, we conducted the Augmented Dickey-Fuller

(ADF) test on our economic sentiment variables (Onatski & Wang, 2021). The results revealed that all variables, except ECORPREM and TERMSPRE, exhibited non-stationarity at the 1% significance level in their levels but exhibited stationarity after taking the first difference, as illustrated in Table 2. Thus, our data meets the necessary stationarity criteria for conducting further econometric analyses, ensuring the reliability and validity of our findings.

Table 2. Augmented Dickey-Fuller Test results

Macro-Economic Variable	Dickey-Fuller Test (ADF) at Level		Dickey-Fuller Test (ADF) at First Difference	
	t-statistic	Probability	t-statistic	Probability
BSE500	1.195564	0.9981	-11.30962	0.0000
FDI	-1.015038	0.7468	-10.21141	0.0000
ECORPREM	-12.07306	0.0000	-9.370362	0.0000
OILPRICE	-1.970298	0.2997	-8.624389	0.0000
LIQECO	0.865333	0.9948	-15.94898	0.0000
INFLAT	0.151128	0.9685	-6.613819	0.0000
PLR	-1.919512	0.3226	-11.65925	0.0000
TERMSPRE	-10.17191	0.0000	-9.055126	0.0000
IIP	-2.662979	0.0831	-6.948888	0.0000
SHORTINT	-0.758216	0.8272	-14.02561	0.0000
EXRATE	-1.951435	0.3081	-8.763556	0.0000
FEXRES	1.767811	0.9997	-6.178234	0.0000
GDP	1.093230	0.9973	-8.781453	0.0000

Source: Author's own compilation in EViews 12

All the macroeconomic variables have been taken as independent variables and market return as the dependent variable. S&P BSE 500 percentage return has been used as a proxy for the market return.

5 Results and Discussion

Tables 3 to 8 present the results of our analysis. The findings indicate a significant relationship between the market return and six variables: BSE500, ECORPREM, FDI, GDP, INFLAT, PLR, and SHORTINT. Notably, the coefficient of determination (R^2) is calculated to be 0.998503, exceeding the threshold of 0.6. This suggests that the model possesses substantial explanatory power. Additionally, the adjusted R^2 value, standing at 0.998309, further supports the model's credibility by accounting for the number of predictors, thereby reinforcing the robustness of our findings.

Note: It may be argued that the ARDL model cannot be applied when the endogenous variable is stationary. It is worth mentioning here that the ARDL model can be applied to variables whether they are I(0) or I(1) (Pesaran & Shin, 1996; Wan Omar, Hussin, & Ali G H, 2015).

The F-statistic for the ARDL model is significant at the 5% level, indicating that the coefficients of the variables are unequal and the model is robust. Our findings reveal that the market return (BSE500) is significantly influenced by several macroeconomic variables, specifically ECORPREM (Economic Premium), FDI (Foreign Direct Investment), GDP (Gross Domestic Product), INFLAT (Inflation), PLR (Prime Lending Rate), and SHORTINT (Short-term Inter-

Table 3. ARDL Model Summary: BSE Sensex Percentage Return and Economic Sentiment Variables

Variable	Coefficient	Std. Error	t-Statistic	Prob.
BSE500(-1)	1.138032	0.089568	12.70578	0.0000*
BSE500(-2)	-0.502545	0.131275	-3.828188	0.0002*
BSE500(-3)	0.666071	0.130838	5.090810	0.0000*
BSE500(-4)	-0.273307	0.095130	-2.872973	0.0049*
ECORPREM	103.9422	3.281604	31.67421	0.0000*
ECORPREM(-1)	-8.201485	10.15928	-0.807290	0.4213
ECORPREM(-2)	44.30375	9.968495	4.444377	0.0000*
ECORPREM(-3)	-26.89330	10.13953	-2.652324	0.0092*
FDI	0.001778	0.001249	1.423056	0.1576****
FDI(-1)	-0.002349	0.001280	-1.835812	0.0691**
FDI(-2)	0.000235	0.001242	0.189501	0.8501
FDI(-3)	0.002066	0.001234	1.673737	0.0970**
FDI(-4)	0.003689	0.001269	2.907485	0.0044*
GDP	-0.000939	0.000623	-1.506373	0.1349***
GDP(-1)	0.002039	0.001094	1.862913	0.0652**
GDP(-2)	-0.003698	0.001067	-3.465576	0.0008*
GDP(-3)	0.001892	0.000613	3.086868	0.0026*
INFLAT	-18.09582	19.91211	-0.908785	0.3655
INFLAT(-1)	20.45295	35.43837	0.577141	0.5650
INFLAT(-2)	-35.79029	36.58308	-0.978329	0.3301
INFLAT(-3)	40.15737	21.49529	1.868194	0.0644**
PLR	260.4461	81.10560	3.211198	0.0017*
SHORTINT	-321.8570	62.17332	-5.176770	0.0000*
SHORTINT(-1)	208.5495	76.14149	2.738974	0.0072*
SHORTINT(-2)	-217.6355	77.64166	-2.803077	0.0060*
SHORTINT(-3)	216.7375	77.43717	2.798882	0.0061*
SHORTINT(-4)	-119.8127	60.65755	-1.975231	0.0508**
C	-1325.185	765.2334	-1.731740	0.0861**

est Rate). Each of these variables exhibits distinct lag effects on the market return. The impact of individual variables is as follows:

- BSE500 Lags: The market return itself shows a significant positive correlation with its first and third lags and a significant negative correlation with its second and fourth lags. This indicates that past market performance is a strong predictor of future returns.
- ECORPREM: Economic Premium displays a mixed impact on market returns. It has a significant positive relationship at the current and second lag values but shows a significant negative relationship at the first and third lags.
- FDI: Foreign Direct Investment positively influences market returns at the third and fourth lags, suggesting that past FDI inflows contribute to future market performance. However, it has a negative impact at the first lag.
- GDP: GDP demonstrates a complex relationship with market returns. It negatively affects returns for the current period and the second lag, while positively influencing returns at the

first and third lags.

- INFLAT: Inflation shows a positive influence on market returns at the third lag, suggesting that higher inflation rates may lead to increased market returns after a lag.
- PLR: The Prime Lending Rate is positively correlated with market returns in the contemporaneous period, indicating that higher lending rates may boost market performance immediately.
- SHORTINT: Short-term Interest Rates exhibit a nuanced impact, with negative associations at the second and fourth lags and positive associations at the first and third lags. This implies that changes in short-term interest rates have varied effects on market returns over different time periods.

Among the economic sentiment variables, those with p-values greater than 0.20 include EXRATE (Exchange Rate), FEXRES (Foreign Exchange Reserves), IIP (Index of Industrial Production), LIQECO (Liquidity in the Economy), OILPRICE (Oil Prices), and TERMSPRE (Terms Spread) at their respective lags (see Table 3). These variables fail to reject the null hypothesis, indicating that they do not have a statistically significant impact on market returns within the context of this model.

The Durbin-Watson statistic is calculated as 2.103402, indicating no autocorrelation in the model. To ensure model robustness, we conducted various tests in EViews 12, including analysis of actual, fitted, and residual graphs, serial correlation tests, heteroskedasticity tests, and CUSUM tests. Figure 1 demonstrates that the fitted values of the BSE500 closely match the actual values, confirming the reliability of our model.

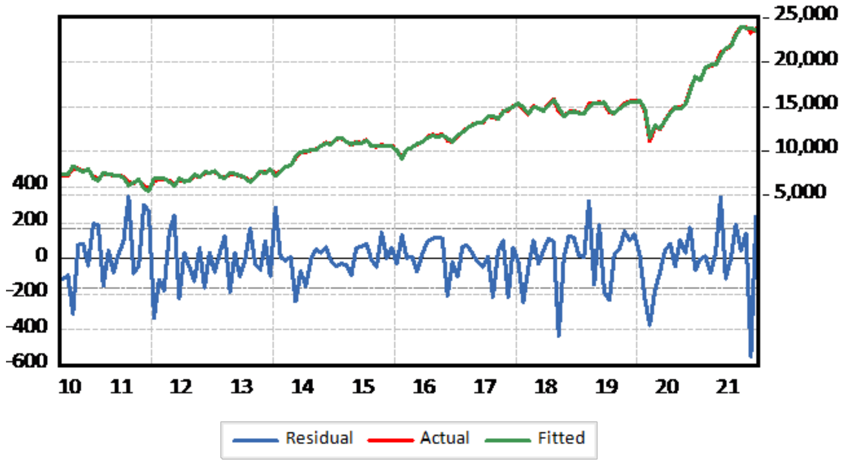

Figure 1. Residual, Fitted, and Actual Values
Source: Developed by the authors, 2024

The results from the Breusch-Godfrey Serial Correlation LM test, as presented in Table 4, indicate that the computed probability values (0.1574 and 0.0960) exceed the conventional significance level of 0.05. This finding suggests that we do not have sufficient evidence to reject the null hypothesis, which asserts the absence of serial correlation in the model. Therefore, we accept the null hypothesis, concluding that our model does not suffer from issues related to serial correlation. Similarly, the outcomes of the Breusch-Pagan-Godfrey heteroskedasticity test, detailed in Table 4, reveal probability values (0.1518, 0.1667, and 0.1159) that exceed the 0.05 significance threshold. This indicates our inability to reject the null hypothesis of homoscedasticity. Hence, we accept the null hypothesis, confirming that our model exhibits equal variance (homoscedasticity).

Furthermore, the Ramsey RESET test confirms the absence of specification errors in our model. This assures that all relevant variables have been appropriately included, the functional form of the model is correctly specified, and there is no serial correlation between the independent variables and the error term.

In summary, the thorough examination of serial correlation and heteroskedasticity, as detailed in Table 4, underscores the validity of our model by confirming its freedom from these potential issues. Detection of serial correlation or heteroskedasticity could compromise the reliability of the model's results.

Table 4. Results of Serial Correlation and Heteroskedasticity Test

Breusch-Godfrey Serial Correlation LM Test Statistic	Value	Prob.
F-statistic	1.881106	0.1574
Obs*R-squared	4.687386	0.0960
Heteroskedasticity Test Statistic	**Value**	**Prob.**
F-statistic	1.328397	0.1518
Obs*R-squared	35.11011	0.1667
Scaled explained SS	37.13769	0.1159
Ramsey RESET Test Statistic	**Value**	**Prob.**
t-statistic	1.717835	0.0887
F-statistic	2.950956	0.0887

The stability of the model is assessed using Cumulative Sum of Recursive Residuals (CUSUM) tests. In Figure 2, the blue line consistently falls within the upper and lower bounds marked by the two red lines. This observation indicates that the model maintains stability throughout the estimation process up to lag 4.

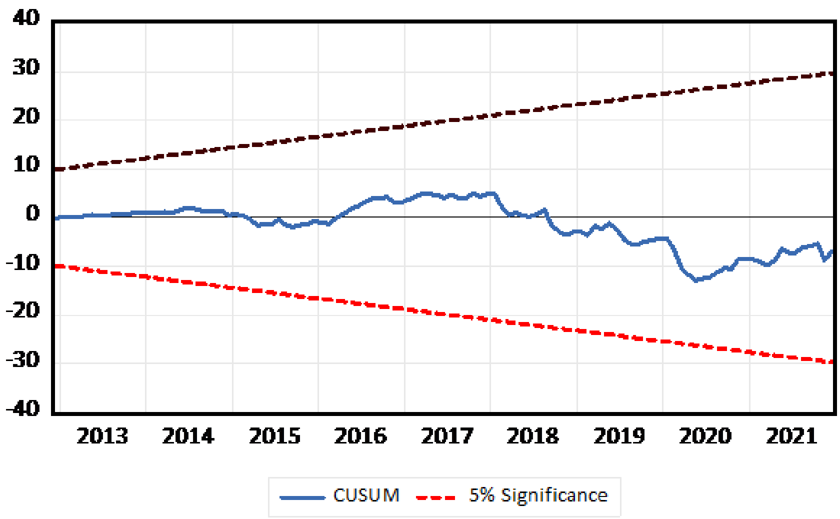

Figure 2. CUSUM Test Results
Source: Developed by the authors, 2024

The bounds testing approach to cointegration is used to determine the existence of a long-run relationship between the variables. This involves computing the F-statistic and comparing it with critical values provided by Pesaran and Shin's (1996). We conducted an analysis using the

ARDL bound test to examine the long-term relationship between Indian stock market returns and sentiment sub-indices. In this test, the F-statistic is crucial: if it exceeds the upper bound value, it indicates the presence of cointegration. If it falls between the upper and lower bound values, the result is inconclusive. A F-statistic lower than the lower bound value suggests no cointegration. From the results presented in Table 5, the computed F-statistic (Wald test) is 5.682638. This finding suggests a significant relationship between returns and sentiment sub-indices, confirming an optimal delay in the relationship.

Table 5. Bound Test Results

Test Statistic	Value	Signif.	I(0)	I(1)
F-statistic	5.682638	10%	1.92	2.89
k	7	5%	2.17	3.21
		2.5%	2.43	3.51
		1%	2.73	3.9

Source: Author's own compilation in EViews 12

If cointegration is established, the long-run coefficients are estimated to understand the impact of economic sentiment on market returns over the long term. The Error Correction Model (ECM) is then constructed to capture short-term dynamics and the speed of adjustment towards equilibrium. The F-statistic in Table 6 surpasses the upper bound for integrated of order one (I(1)), confirming the existence of an independent convergence vector between Indian stock market returns and sentiment sub-indices, substantiating a long-run relationship. Notably, the results exhibit statistical significance across all levels (1%, 2.5%, 5%, and 10%) as shown in Table 6.

Table 6. Error Correction Model Results

Test Statistic	Value	Signif.	I(0)	I(1)
F-statistic	5.682638	10%	1.92	2.89
K	7	5%	2.17	3.21
		2.5%	2.43	3.51
		1%	2.73	3.9

Source: Author's own compilation in EViews 12

Regarding the individual economic sentiment variables, those with a p-value less than 0.20, namely ECORPREM, FDI, GDP, INFLAT, PLR, and SHORTINT, are considered relevant in explaining market return. Conversely, variables such as EXRATE, FEXRES, IIP, LIQECO, OILPRICE, and TERMSPRE, with p-values exceeding 0.20, fail to reject the null hypothesis, indicating their lack of significant impact on market return. Therefore, these economic sentiment variables are deemed irrelevant in explaining market return. The long-run coefficients presented in Table 7 reveal that economic sentiment variables ECORPREM, GDP, PLR, and SHORTINT significantly influence market return at the 20% significance level. In contrast, FDI and INFLAT show statistical insignificance, indicating no long-term correlation of these variables with market return.

We conducted an error correction form test to assess the dynamic adjustment of our model. As shown in Table 8, the estimation includes short-run coefficients for market returns, structural

Table 7. Long-Run Coefficients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
ECORPREM	-4005.280	2112.446	-1.896039	0.0606**
FDI	-0.191801	0.149133	-1.286104	0.2000
GDP	0.024994	0.012610	1.982100	0.0500*
INFLAT	-238.0205	295.8129	-0.804632	0.4228
PLR	-9219.167	5004.434	-1.842200	0.0682**
SHORTINT	8283.682	5170.302	1.602166	0.1120***
C	46908.38	40352.88	1.162454	0.2476

* Significant at 5%, ** Significant at 10%, *** Significant at 15%, **** Significant at 20%
(Source: Author's own compilation in EViews 12)

variables, and the CointEq(-1) value. The CointEq(-1) value is -0.828251, with a p-value of 0.0000, indicating significant monotonic adjustment. This suggests that the system corrects its previous period at a speed of 82.8251% per month, corresponding to an adjustment duration of approximately 1.21 months (1/0.828251).

Furthermore, the t-statistic records a notable value of -7.409278, indicating the coefficient's high significance. Moreover, the values of r2 and adjusted r2 stand at 0.943634 and 0.933999, respectively. These figures indicate that 94.36% and 93.39% of the variation in market returns can be explained by the regressors, specifically the sentiment sub-indices.

The Durbin-Watson statistic serves as a measure to identify autocorrelation within the residuals of a regression analysis. In our model, the calculated Durbin-Watson value is 2.103402, indicating the absence of autocorrelation among the variables. This value falls within the acceptable range of 0 to 4, suggesting that the residuals do not display significant serial correlation. Hence, we can conclude that our model meets the assumption of no autocorrelation in the residuals.

6 Limitations

While this study provides valuable insights into the relationship between economic sentiment and market returns in the Indian stock market, there are a few limitations to consider:

- Data Scope: The study relies on data from a specific period and market, which may limit the generalizability of the findings to other time frames or markets. Future research could extend the analysis to different periods or compare results across multiple markets to enhance generalizability.
- Sentiment Measurement: The measurement of investor sentiment, while robust, may not capture all nuances of market sentiment. Incorporating additional sentiment indicators or alternative measurement methods in future studies could provide a more comprehensive understanding.
- Model Assumptions: The ARDL model, used for its strengths in handling non-stationary data, does come with certain assumptions. Exploring alternative econometric models or methodologies could help validate the findings and address potential model-specific limitations.

  These limitations do not detract from the study's contributions but suggest avenues for further research to build on and refine the insights presented.

Table 8. Error Correction Form

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(BSE500(-1))	0.109781	0.086025	1.276148	0.2046
D(BSE500(-2))	-0.392763	0.084587	-4.643320	0.0000*
D(BSE500(-3))	0.273307	0.081276	3.362703	0.0011*
D(ECORPREM)	103.9422	2.878143	36.11434	0.0000*
D(ECORPREM(-1))	-17.41045	11.80178	-1.475239	0.1430***
D(ECORPREM(-2))	26.89330	8.671314	3.101410	0.0025*
D(FDI)	0.001778	0.001071	1.660770	0.0996**
D(FDI(-1))	-0.005990	0.001379	-4.342767	0.0000*
D(FDI(-2))	-0.005755	0.001382	-4.162916	0.0001*
D(FDI(-3))	-0.003689	0.001106	-3.333908	0.0012*
D(GDP)	-0.000939	0.000555	-1.690861	0.0937**
D(GDP(-1))	0.001806	0.000638	2.831860	0.0055*
D(GDP(-2))	-0.001892	0.000547	-3.459916	0.0008*
D(INFLAT)	-18.09582	18.23964	-0.992115	0.3233
D(INFLAT(-1))	-4.367075	21.62497	-0.201946	0.8403
D(INFLAT(-2))	-40.15737	19.28999	-2.081773	0.0397*
D(SHORTINT)	-321.8570	52.64583	-6.113627	0.0000*
D(SHORTINT(-1))	120.7107	55.17167	2.187911	0.0308*
D(SHORTINT(-2))	-96.92481	53.91251	-1.797817	0.0750**
D(SHORTINT(-3))	119.8127	53.25776	2.249676	0.0265*
CointEq(-1)*	-0.828251	0.003813	-7.409278	0.0000*
R-squared	0.943634	Mean dependent var	121.1507	
Adjusted R-squared	0.933999	S.D. dependent var	617.4932	
S.E. of regression	158.6380	Akaike info criterion	13.11039	
Sum squared resid	2944423.	Schwarz criterion	13.55585	
Log likelihood	-883.6172	Hannan-Quinn criter.	13.29142	
Durbin-Watson stat	2.103402			

* Significant at 5%, ** Significant at 10%, *** Significant at 15%, **** Significant at 20%
(Source: Author's own compilation in EViews 12)

7 Conclusion

This analysis highlights the importance of considering lag effects and the multifaceted nature of economic indicators when evaluating market returns (as measured by the BSE S&P 500 Index) using ARDL modeling. The findings support the alternative hypothesis (H_1) that there is a significant relationship between economic sentiment and market returns, refuting the null hypothesis (H_0) of no significant relationship. Our results are in line with Rohilla and Tripathi's (2022). Also, findings contribute to a deeper understanding of how various macroeconomic factors influence market behavior, offering practical insights for investors, policymakers, and researchers.

7.1 Key Findings

- High Correlation: Economic sentiment proxies, particularly economic risk premium (ECORPREM), foreign direct investment (FDI), gross domestic product (GDP), inflation rates (INFLAT), prime lending rate (PLR), and short-term interest rates (SHORINT) exhibit a high degree of correlation with market returns.
- Significant Short-Term Effects: The ARDL model reveals that changes in economic sentiment proxies have immediate impacts on market returns, reflecting the sensitivity of the stock market to economic conditions.
- Stable Long-Term Relationship: The cointegrating equation confirms a stable long-term equilibrium relationship, indicating that the market returns eventually align with the underlying economic sentiment.
- Error Correction Mechanism: The significant and negative error correction term (ECT) suggests that short-term deviations from the equilibrium are corrected over time, reinforcing the stability of the long-term relationship.

7.2 Policy Implications

The results of this study have important implications for policymakers, investors, and market analysts:

- Market Regulation: Regulators could consider sentiment indicators when formulating policies to stabilize financial markets.
- Policy Formulation: Policymakers can use the identified economic sentiment proxies to gauge market reactions to economic policies and make informed decisions to stabilize the market.
- Economic Forecasting: Policymakers could incorporate sentiment analysis into economic forecasting models to better anticipate market movements.
- Investment Strategies: Investors can enhance their portfolio management strategies by incorporating economic sentiment indicators to predict market trends and make better investment decisions.
- Market Analysis: Market analysts can leverage the findings to develop more accurate market forecasts and advise clients based on a comprehensive understanding of economic sentiment.

7.3 Future Research

This study opens avenues for future research to extend the analysis to other emerging markets and examine the role of additional macroeconomic variables in influencing market returns. Further research can also explore the impact of global economic sentiment on domestic markets, providing a holistic view of the interconnectedness of global financial systems. In conclusion, this study underscores the critical role of economic sentiment in shaping market returns in the Indian stock market. By employing the ARDL approach, it provides robust evidence of the dynamic interplay between economic sentiment and market performance, offering valuable insights for various stakeholders in the financial ecosystem.

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Appendix

Estimation Command:

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ARDL BSE500 ECORPREM EXRATE FDI GDP INFLAT PLR SHORTINT @

Estimation Equation:

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BSE500 = C(1)*BSE500(-1) + C(2)*BSE500(-2) + C(3)*BSE500(-3) + C(4)*BSE500(-4) + C(5)*ECORPREM + C(6)*ECORPREM(-1) + C(7)*ECORPREM(-2) + C(8)*ECORPREM(-3) + C(9)*EXRATE + C(10)*FDI + C(11)*FDI(-1) + C(12)*FDI(-2) + C(13)*FDI(-3) + C(14)*FDI(-4) + C(15)*GDP + C(16)*GDP(-1) + C(17)*GDP(-2) + C(18)*GDP(-3) + C(19)*INFLAT + C(20)*INFLAT(-1) + C(21)*INFLAT(-2) + C(22)*INFLAT(-3) + C(23)*PLR + C(24)*SHORTINT + C(25)*SHORTINT(-1) + C(26)*SHORTINT(-2) + C(27)*SHORTINT(-3) + C(28)*SHORTINT(-4) + C(29)

Substituted Coefficients:

=========================

BSE500 = 1.1380317*BSE500(-1) - 0.502544670*BSE500(-2) + 0.666070549*BSE500(-3) - 0.273307092*BSE500(-4) + 103.942218944*ECORPREM - 8.201484874*ECORPREM(-1) + 44.3037524602*ECORPREM(-2) - 26.893302*ECORPREM(-3) + 11235.6120879*EXRATE + 0.001777991*FDI - 0.0023494395*FDI(-1) + 0.000235308*FDI(-2) + 0.00206597*FDI(-3) + 0.003688628*FDI(-4) - 0.00093855*GDP + 0.002038524*GDP(-1) - 0.00369800*GDP(-2) + 0.001891933*GDP(-3) - 18.09582204*INFLAT + 20.45294692*INFLAT(-1) - 35.7902944*INFLAT(-2) + 40.1573693*INFLAT(-3) + 260.446101*PLR - 321.85694*SHORTINT + 208.549534*SHORTINT(-1) - 217.63554*SHORTINT(-2) + 216.737515*SHORTINT(-3) - 119.81270*SHORTINT(-4) - 1325.185421

Cointegrating Equation:

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D(BSE500) = 0.0282505*(BSE500(-1) -(-4005.2802*ECORPREM(-1)-397713.69126*EXRATE -0.1918006*FDI(-1)+ 0.024994*GDP(-1) -238.02052*INFLAT(-1)-9219.16665*PLR + 8283.68203*SHORTINT(-1)+46908.382170))