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Investors' Sentiment and Market Return Nexus: An ARDL Approach

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Abstract: *Purpose:* This paper discovers the relationship between investor sentiment and market return over a period of 12 years in the context of Indian stock market. *Design/Methodology/Approach:* Using 23 market and macroeconomic variables, investors' sentiment indices have been created by applying principal component analysis. Further analysis has been done by employing an auto-regressive distributed lag model. *Findings:* Results show that there is a significant positive relationship between investor sentiment and market return. *Practical Implications:* The results of the study are helpful for retail investors, fund managers, and policymakers to gain a better understanding of the Indian stock market and enhance their earnings by incorporating investor sentiment into their decision-making. Further, asset pricing models such as CAPM, the Fama-French three- and five-factor model, and the Carhart factor model need to incorporate investor sentiment for a better explanation of prices. *Originality/Value:* The study proposed a new methodology to measure the investor sentiment of Indian investors. The results have paved the way to spreading the present work in the context of foreign markets such as the BRICS countries.

Keywords: Auto Regressive Distributed Model; Behavioral Finance; Investor Sentiment; Market Return; Principal Component Analysis; Sentiment; Sentiment Index

JEL Classification: G11, G12, G17, G4, G41

1. Introduction

Classical finance disproves the investor's rationality, and behavioural finance approves it. Classical finance literature shows that the prices of shares are random, do not follow any pattern, and cannot be predicted (Fama, 1965; Malkiel, 1973). The capital asset pricing model asserts that the prices of shares reflect all of the available information in the public domain, provided the market is efficient enough. Rational investors always push the market value of the shares towards the present value of the projected cash flows, and arbitrageurs are always there to offset their demands, if any. It seems that the emotions of investors have no role to play in the stock market.

Market participants have made market efficiency and rationality the basis of their decisions for a long time. But the idea of market efficiency and rationality is losing its importance because it has been unable to explain phenomena like Black Monday, the dot-com bubble, and the 2005 global financial crisis.

Modern and behavioural finance challenge the theory of rationality and state that most investors are irrational and follow herd behaviour. These investors keep trying to make money from the bullish market, but as soon as the bearish trend starts, they are shown the way out of the market. The psychology of these investors influences their behaviour to a great extent. Behavioral finance helps in understanding the psychology and decision-making processes of investors. Behavioral finance takes into account the estimation and bias frameworks for asset pricing.

In India, the work on the relationship between sentiment and return is in its infancy. We intend to extend the existing relationship between sentiment and return by developing a methodology for identifying the best proxies for sentiment and measuring it using sub-indices. One advantage of these sub-indices is that they aid in understanding the sentiment-return link, which, if present, can lead to the hypothesis that sentiment can forecast the stock market.

The present study is an attempt to identify the proxies for the sentiment of Indian investors and measure it by constructing sentiment sub-indices. After an extensive study of the literature, 23 proxies for the sentiment have been identified, and 11 sub-indices have been created by applying principal component analysis. These sub-indices represent the sentiment of Indian investors. Further, the short- and long-run sentiment-return linkage has been examined using the auto-regressive distributed lag model (ARDL).

2. Review of Literature

Since 1965, a lot of studies have been conducted on the effect of changes in the behavior of investors on the market return and stock prices. According to Fama (1965), share prices do not follow any pattern and are completely independent. Malkiel (1973) propounded the random walk theory, which describes share price movement as a random walk that cannot be predicted. Shiller (1981) states that investors are irrational and share prices are affected not only by fundamentals but by other factors as well. Black (1986) describes these investors as "noise traders" because they act irrationally. It is worth noting that these investors have limited access to private information. Chen, Roll & Ross (1986) hold that macroeconomic factors are also responsible for the changes in share prices. According to De Long, Shleifer, Summers & Waldmann (1990), irrational noise traders achieve high unanticipated returns by influencing asset prices with their random gut instincts and beliefs.

Several studies have shown that investor sentiment influences market returns to a great extent (Tversky & Kahneman, 1981; Thaler & Shefrin, 1981; Shefrin & Statman, 1984). Thus, it can be said that sentiment plays a vital role in the stock market.

Fisher and Statman (2000) chose three groups of investors, *viz.*, large, medium, and retail, to measure sentiment and proposed that there is a strong correlation between sentiment and returns of large and small-cap shares. It was found that aggregate sentiment helps in predicting the market's return.

Baker and Wurgler (2004b) decoded sentiment and proposed that it can be measured using proxies such as close-end fund discount in their seminal work. In their work, a significant relationship between the catering view (Baker & Wurgler, 2004a) and the propensity to pay dividends was reported. Investors prefer dividend-paying stocks in times of negative sentiment and riskier stocks in times of positive sentiment. Brown & Cliff (2004) define "sentiment" as the discrimination that investors have in the valuation of assets at times of extreme optimism and pessimism.

Kumar & Lee (2006) used the data of individual (retail) traders to analyze the impact of retail trading on stock returns. Sentiment emerged as an important factor in explaining the return of the currency. According to Wang, Keswani & Taylor (2006), market return and volatility cause sentiment, but not the other way around. The study failed to establish any linkage between sentiment and return or volatility.

Baker & Wurgler (2006), in their groundbreaking work on sentiment, gave a conceptual framework describing the methodology to measure investor sentiment using some specific proxies such as closed-end fund discount, number of IPOs, market turnover, etc. Baker & Wurgler (2007) explicitly measured investor sentiment using the proxies they proposed and showed that it could explain the market return to a great extent.

In India, Sehgal, Sood & Rajput (2009) tried to identify the possible factors that could affect investors' sentiment using a structured questionnaire. Also, the study defined sentiment as an understanding of investors' behavior affecting share market activities. Sehgal, Sood & Rajput (2010) used the vector autoregression model to show that sentiment is closely associated with the market return, but the cause-and-effect relationship is not there.

Dash and Mahakud (2013a) examined the impact of sentiment on industrial returns using the Prowess database's industry groups. The study showed that not all industries are sensitive to sentiment. Fund managers can earn higher returns by investing in the shares of industries that are less sensitive to sentiment at a time of low sentiment and vice versa.

Jitmaneeroj (2017) suggested that the price-earnings ratio is a better proxy for investor sentiment, and researchers shall try to establish a relationship between these two. Pandey & Sehgal (2019) showed that the aggregate sentiment indices explained asset prices better when combined with the Fama-French five-factor model.

Companies can decide on the timing of their initial public offerings. Gupta & Maurya (2021) showed that companies raise more funds when IPOs are launched at times of high sentiment.

The study by Sharma (2021) showed a link between sentiment and the volatility of industrial returns. The study reported that for industrial volatility modeling, EGARCH is the most suitable model in the context of the National Stock Exchange of India.

The study of the literature shows that most of the researchers have worked on the relationship between sentiment and return, especially in the context of western and developed economies. But in India, this work is still in its infancy. Researchers have worked with shorter durations and fewer proxies, which we think is a research gap. The use of longer durations and a higher number of proxies can give impressive results.

The present research work attempts to contribute to the existing literature on the sentiment-return relationship using a longer duration and a higher number of proxies so that retail investors, policymakers, and fund managers in the Indian equity market can make better decisions.

3. Objectives and Hypotheses of the Study

3.1. Objectives of the Study

The major objectives are—

1. To represent investor sentiment using sentiment sub-indices
2. To examine the sentiment-return relationship.

3.2. Hypotheses of the Study

The following hypotheses have been tested—

H_{01}: There is no long-run relationship between market return and sentiment sub-indices.

Note: Secondary hypotheses have also been set and can be made available on request.

4. Research Methodology

4.1. Proxies to the Sentiment

There is no concrete answer to the question of how many proxies represent sentiment. Researchers have used some selected proxies to measure sentiment (Baker & Wurgler, 2006; Sehgal *et al.*, 2010). There is no doubt that the survey method is the best means of measuring sentiment, but it has some limitations, such as issues in the data collection, delays in the data collection, *etc*. Most of the research measures sentiment through proxies. The use of proxies provides some benefits, such as the authentic source of the data and generalization.

Different studies used different numbers of proxies (Rohilla & Tripathi, 2022a; Rohilla, 2022b; Rohilla & Tripathi, 2022c). Based on the study of literature and the availability of data, we have selected 32 proxies that are proxies for the sentiment of investors (details of the selected proxies can be made available on request). Some of these proxies are theoretical in nature and must be validated after analysis.

4.2. Data Set and Time Frame

The monthly data of selected proxies has been collected from various websites, *viz.*, CSO, BSE, CDSL, Department for Promotion of Industry and Internal Trade, IMF, indexmundi.com, NSE, Federal Reserve Bank of St. Louis, OFX, RBI, and SEBI. A total of 141 monthly observations of each proxy, ranging from April 2010 to December 2021, have been collected.

Multicollinearity is a situation when independent variables are correlated with each other. It makes the model biased and creates problems with model fitting and interpreting the results. To identify the presence of multicollinearity in our dataset of 32 proxies, we have calculated Carl Person's coefficient of correlation (a value of more than 0.70 is a high degree of correlation (Cooper & Schindler, 2014, p. 537)) in the EViews 12.

We have removed nine variables, *viz.*, PER, DIVYIELD, RTVOL, INFLAT, PLR, SHORTINT, EXRATE, FEXRES, and GDP. We have removed these variables using a two-step process. In the first step, we checked for a high correlation between the two variables. When two variables were found to be highly correlated, the next step was to remove variables not used as proxies for sentiment in the existing literature.

By calculating the Z-score, the data is standardized because it improves the compatibility among different variables with different scales and is a prerequisite for using PCA. The first principal component may dominate others because variables used for the calculation of the first component may have a high variance due to different scales of measurement, and standardization prevents this problem.

A time series may be stationary or non-stationary. When the series is non-stationary, model development is difficult, and such a model has no forecasting power (Onatski & Wang, 2021). All the time series were tested for stationarity using the Augmented Dicky Fuller and Phillips Perron Test at a 1% level of significance. The ADF test reported that 11 series are non-stationary series at the level, and the Phillips-Perron test reported 10 series as non-stationary at the level. To make the time series stationary, the first order difference was taken, and after losing one observation, stationarity was again checked at the 1% level of significance using the ADF and Phillips-Perron test. At the 1% level of significance, the ADF test reported MKTTURN as non-stationary at the first difference, whereas the Phillips-Perron test reported it stationary at the first difference. We have accepted the results of the Phillips-Perron test. The results are not provided here due to the brevity of the space but can be made available on request.

4.3. Measurement of Investors Sentiment

To the best of our knowledge, there are no common proxies for measuring IS, and no literature is available that limits the number of proxies that can be used to measure IS. After studying the extant literature, 32 proxies were considered, and after analyzing their inter-correlations, nine proxies were dropped. Then, using principal component analysis in IBM SPSS 20, 23 proxies are reduced to 11 principal components (PCs), and these components are saved as variables (detailed results of the principal component analysis can be made available on request). These 11 PCs are our investor sentiment sub-indices and represent the sentiment of Indian investors. Also, to make the 11 sub-indices meaningful, these were named after some brainstorming.

The KMO Test evaluates whether the data are appropriate for factor analysis. A value less than 0.6 means that the sample is inadequate and needs remedial action. The Kaiser-Meyer Olkin (Kaiser & Rice, 1974) came out to be 0.835, showing that principal component analysis of the variables is a good idea.

We have used the variance extraction rule and selected 11 components. The variance extraction rule suggests that components with an eigenvalue greater than 0.7 shall be selected (Bandalos & Boehm Kaufman, 2009, pp. 61–67). Selected components explain 78.252% of the variation, which is close to 80% and acceptable for a model to be valid.

After identifying maximum factor loadings, the proxies have been grouped based on their respective principal components (Table 2) and named accordingly.

Table 1: KMO and Barlett's Test

Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy		0.835
Bartlett's Test of Sphericity	Approx. Chi-Square	1043.813
	Sig.	0.000

Source: Author's calculation based on PCA results obtained in IBM SPSS 20

Table 2: Eigenvalues and the Total Variance Explained

Component Characteristics			
Principal Components	*Eigenvalues*	*Proportion Variance*	*Cumulative*
PC1	3.757	16.336%	16.336%
PC2	2.826	12.287%	28.623%
PC3	1.901	8.263%	36.887%
PC4	1.554	6.755%	43.641%
PC5	1.434	6.234%	49.876%
PC6	1.343	5.837%	55.713%
PC7	1.179	5.126%	60.839%
PC8	1.109	4.820%	65.659%
PC9	1.070	4.652%	70.311%
PC10	.972	4.225%	74.535%
PC11	.855	3.717%	78.252%

Extraction Method: Principal Component Analysis with Variance Extraction Criterion
Source: Author's calculation based on PCA results obtained in IBM SPSS 20

We have saved the 11 principal components as variable series in IBM SPSS 20, and these 11 series are our investor sentiment sub-indices. Further, these 11 sub-indices are assigned meaningful names. We have checked the maximum loading for each proxy and identified the principal component corresponding to that maximum loading. The rotated component matrix and factor loadings are in Table 3.

After identifying the maximum loading, the proxies have been grouped based on their respective principal components. Meaningful names must be assigned to the sub-indices before we draw any inferences from them. The 11 principal components obtained have been named in Table 4.

Sentiment sub-indices are used for the quantification of investor sentiment. Sentiment indices derived in this manner can be used to determine their relationship with market returns.

Table 3: Maximum Factor Loadings of the Proxies and Corresponding Principal Components

Variables	*Components*										
	1	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*11*
MKTTURN	.183	**.814**	.045	-.002	.224	.083	.021	-.057	.189	-.100	.002
NUMTRADE	.049	**-.786**	.138	-.031	.115	.051	.040	-.135	-.018	-.049	-.012
TRADEQTY	.020	**.791**	.326	.050	.095	.125	.053	-.208	-.121	.123	-.041
TVR	-.016	.087	.126	-.038	.117	.143	.028	.032	**.866**	.229	-.026
ADR	-.161	.040	**.858**	.009	.057	.066	-.049	-.080	.078	-.093	.042
COMPTRAD	**-.583**	.341	-.041	.473	-.130	-.238	-.037	.095	.066	.175	.004
VIX	**.751**	.095	.112	.094	-.184	.351	.053	-.099	-.089	.104	-.027
FPI	**-.732**	.014	.274	-.061	.096	.167	-.153	-.121	-.084	.044	.110
PCR	-.035	.106	-.201	-.034	-.109	**.798**	-.013	-.082	.207	-.062	-.030
PBR	-.168	.052	.443	**-.692**	.060	.002	-.003	.068	.193	-.148	-.038
BSI	.273	-.020	-.040	.025	-.122	-.091	-.013	**.819**	.074	-.027	.004
FDI	-.159	-.045	.137	.010	.166	.545	.081	**.552**	-.398	.139	-.017
HLI	-.060	.044	**.789**	-.114	-.099	-.264	.076	.075	.014	.036	-.073
EQRATIO	.211	.139	.013	-.075	-.044	.096	**.772**	-.211	-.042	.043	.073
NIFPO	-.071	-.119	.004	.056	.102	-.084	**.802**	.209	.058	-.172	-.018
ECORPREM	**-.842**	-.054	.004	.006	-.132	.071	.054	-.120	-.026	-.105	-.074
XRETMP	.087	.041	-.064	-.093	-.002	-.025	-.115	.003	.198	**.888**	-.046
OILPRICE	-.031	-.023	.035	.124	**.840**	-.113	.022	-.054	.058	-.030	-.091
BDEPMCAP	**.600**	-.432	-.215	.332	-.051	-.020	-.002	-.012	-.193	.271	.061
EQMF	**.750**	.184	-.168	.044	.168	-.127	.050	.138	.040	-.047	.049
LIQECO	.061	.043	.069	**.815**	.070	.012	-.007	.049	.052	-.198	.011
TERMSPRE	.015	-.013	-.021	.030	-.021	-.030	.043	.000	-.022	-.041	**.979**
IPI	.231	.361	-.112	-.280	**.636**	.104	.059	-.038	.063	.059	.165

Extraction Method: Principal Component Analysis
Rotation Method: (Rotation converged in 16 iterations) Varimax with Kaiser Normalization
(*Source:* Author's calculation based on PCA results obtained in IBM SPSS 20)

4.4. Sentiment and Market Return Relationship

Pesaran, Shin & Smith (2001) introduced the ARDL approach. We have used this model in Eviews 12 to analyze the long-run relationship between stock market return and sentiment sub-indices in the Indian stock market. We have used the methodology proposed by Tripathi and Kumar (2015). An auto-regressive distributed lag model is defined as follows—

$$\text{ARDL (1, 1) model: } y_t = \mu + \alpha_1 y_{t-1} + \beta_0 x_t + \beta_1 x_{t-1} + u_t \quad (1)$$

Where,

y_t = Stationary variable; x_t = Stationary variable; u_t=White noise

Stationarity of data is a prerequisite for most of the advanced econometric techniques, and the ARDL model is one of them (Tripathi & Kumar, 2015a; Tripathi & Kumar 2015b). A series is said to be stationary if its mean, variance, and auto-covariance are time-invariant. We have used the Augmented Dickey-

Table 4: Naming Sentiment Sub-Indices

Principal Components	*Proxies*	*Name of the Principal Component*
PC1	COMPTRAD	Market and Economic Variables
	VIX	
	FPI	
	ECORPREM	
	BDEPMCAP	
	EQMF	
PC2	MKTTURN	Market Ratios
	NUMTRADE	
	TRADEQTY	
PC3	ADR	Advance-Decline Ratio and High-Low Index
	HLI	
PC4	PBR	Price to Book Value Ratio and Liquidity in the Economy
	LIQECO	
PC5	OILPRICE	Oil Price and Industrial Production Index
	IPI	
PC6	PCR	Put-Call Ratio
PC7	EQRATIO	The Ratio of Equity in Total Issues and Total Number of Issues
	NIFPO	
PC8	BSI	Buy-Sell Imbalance and Foreign Direct Investment
	FDI	
PC9	TVR	Trading-Volume Ratio
PC10	XRETMP	Extra Return on Market Portfolio
PC11	TERMSPRE	Term-Spread

Source: Author's own compilation

Fuller (Fuller, 1976) test and the Phillips Perron test to check the stationarity of our sentiment sub-indices (Taghizadeh and Ahmadi, 2019; Onatski & Wang, 2021). All the sentiment sub-indices were found to be stationary at level (at a 1% level of significance) since the series of all the original variables were stationary at the first difference (the results of the unit root test applied to the sentiment sub-indices can be made available on request).

5. Results and Data Analysis

5.1. Auto Regressive Distributed Lag Model Equations

Following is the ARDL model equation—

BSE500RETURN=C(1).BSE500RETURN(-1)+C(2).BSE500RETURN(-2)+C(3).BSE500RETURN(-3)+C(4).PC1+C(5).PC1(-1)+C(6).PC1(-2)+C(7).PC1(-3)+C(8).PC2+C(9).PC2(-1)+C(10).PC2(-2)+C(11).PC2(-

3)+C(12).PC3+C(13).PC3(-1)+C(14).PC3(-2)+C(15).PC4+C(16).PC4(-1)+C(17).PC4(-2)+C(18).PC4(-3)+C(19).PC5+C(20).PC5(-1)+C(21).PC5(-2)+C(22).PC5(-3)+C(23).PC6+C(24).PC7+C(25).PC7(-1)+C(26).PC7(-2)+C(27).PC7(-3)+C(28).PC8+C(29).PC8(-1)+C(30).PC8(-2)+C(31).PC9+C(32).PC9(-1)+C(33).PC10+C(34).PC10(-1)+C(35).PC10(-2)+C(36).PC11+C(37) (2)

Note: Lags are given in parentheses.

Following is the ARDL equation with substituted coefficients—

BSE500RETURN=-0.00353191765734.BSE500RETURN(-1)-0.247054131513.BSE500RETURN(-2)+0.389789325857.BSE500RETURN(-3)-0.0502610286975.PC1-0.0258225123103.PC1(-1)-0.0267640966019.PC1(-2)+0.00436380917392.PC1(-3)-0.00818191048201.PC2-0.00464889336185.PC2(-1)+0.00245030397951.PC2(-2)-0.0044579163159.PC2(-3)+0.0102710333635.PC3+0.00495577461479.PC3(-1)+0.00731783993236.PC3(-2)-0.0159367014831.PC4+0.00243055299113.PC4(-1)-0.00524382852742.PC4(-2)+0.00350834617339.PC4(-3)-0.000823271086784.PC5+0.000952864197308.PC5(-1)-0.000905575296089.PC5(-2)+0.0047188007111.PC5(-3)-0.000258152167688.PC6+0.00551336562455.PC7+0.00716711758874.PC7(-1) + 0.00477180656238.PC7(-2)+0.00519967195487.PC7(-3)-0.0112717590098.PC8-0.0106604174566.PC8(-1)-0.00696940083632.PC8(-2)-0.00149225899977.PC9-0.0078181456582.PC9(-1)-0.0144036307152.PC10-0.0121217046281.PC10(-1)-0.0142454409555.PC10(-2)-0.00404906759054.PC11+0.00978111433023 (3)

Where,

PC1=Market and Economic Variables; PC2=Market Ratios; PC3=Advance-Decline Ratio and High-Low Index; PC4=Price to Book Value Ratio and Liquidity in the Economy; PC5=Oil Price and Industrial Production Index; PC6=Put-Call Ratio; PC7=The Ratio of Equity in Total Issues and Total Number of Issues; PC8=Buy-Sell Imbalance and Foreign Direct Investment; PC9=Trading-Volume Ratio; PC10=Extra Return on Market Portfolio; and PC11=Term-Spread

5.2. Auto Regressive Distributed Lag Model

Our ARDL model regresses the S&BP BSE 500 percentage return (dependent) on its own lagged values and on stationary contemporary and lagged values of sentiment sub-indices (independent). The results of the model are in Table 5.

Table 5: ARDL Model for Sentiment Sub-Indices and Market Return

Dependent Variable: BSE500RETURN
Method: ARDL
Dynamic regressors (3 lags, automatic): PC1, PC2, PC3, PC4, PC5, PC6, PC7, PC8, PC9, PC10, and PC11

Variable	*Coefficient*	*Std. Error*	*t-Statistic*	*Prob.*
BSE500RETURN(-2)	-0.247054	0.086583	-2.853393	0.0052*
BSE500RETURN(-3)	0.389789	0.074342	5.243190	0.0000*
PC1	-0.050261	0.002594	-19.37840	0.0000*
PC1(-1)	-0.025823	0.005342	-4.833617	0.0000*
PC1(-2)	-0.026764	0.005598	-4.781425	0.0000*
PC2	-0.008182	0.002356	-3.472220	0.0008*
PC2(-3)	-0.004458	0.002149	-2.074217	0.0406*
PC3	0.010271	0.002539	4.045431	0.0001*
PC3(-2)	0.007318	0.002523	2.899888	0.0046*
PC4	-0.015937	0.003392	-4.698515	0.0000*
PC5(-3)	0.004719	0.002234	2.111906	0.0372*
PC6	-0.000258	0.002096	-0.123191	0.9022
PC7	0.005513	0.002434	2.265262	0.0256*
PC7(-1)	0.007167	0.003034	2.362155	0.0201*
PC7(-3)	0.005200	0.002506	2.074874	0.0405*
PC8	-0.011272	0.002779	-4.055607	0.0001*
PC8(-1)	-0.010660	0.003140	-3.394758	0.0010*
PC8(-2)	-0.006969	0.002998	-2.324455	0.0221*
PC9(-1)	-0.007818	0.002191	-3.567912	0.0006*
PC10	-0.014404	0.002478	-5.813602	0.0000*
PC10(-1)	-0.012122	0.003036	-3.992819	0.0001*
PC10(-2)	-0.014245	0.002774	-5.135012	0.0000*
PC11	-0.004049	0.001782	-2.272813	0.0252*
C	0.009781	0.002231	4.383317	0.0000*
R-squared	0.888359	Durbin-Watson stat		2.027765
Adjusted R-squared	0.848566			
F-statistic	22.32452			
Prob(F-statistic)	0.000000			

* Significant at 5%
Source: Author's calculation based on results obtained in EViews 12

The r^2 of this model is 0.89, and the adjusted r^2 is 0.85. The F statistic is significant at the 5% level of significance, which means that coefficients are not equal. The Durbin-Watson value is 2.027765, which means that there is no autocorrelation in the model (Durbin & Watson, 1971).

Results reveal that Indian stock market returns are significantly explained by themselves (PC1, PC3, PC4, PC5, PC7, PC9, PC10, and PC11). Indian stock market returns have a significant negative relationship with the lagged values of PC1, PC2, PC3, PC4, PC5, PC7, PC8, PC9, PC10, and PC11. There is no evidence that PC6 is related to market returns.

At the first lag, the market return has a negative relationship with itself, but a positive relationship at the second lag.The market return is negatively related to the contemporaneous and lag values of PC1. In the case of the PC3, the relationship between market return and its contemporaneous and lagging values was found to be significantly negative at both the first and third lags.

Return is negatively related to the contemporaneous values of PC4 and positively related to its lagged (third lag) values. Only at the third lagged is PC5 positively related to market return.The market return is positively related to contemporaneous values of PC7 and lagged values (first and third lags).

Return is negatively related to the contemporaneous values of PC8 and the lag values (first and second) of it. In the case of PC9, the relationship is initially negative. Market return has a negative relationship with PC10 (contemporaneous values, values at first and second lag) and PC11 (contemporaneous values).

5.3. Graphical Representation of ARDL Model for Market Return and Sentiment Sub-Indices

Figure 1 graphically represents the ARDL model. The fitted values of Indian stock market returns are close to the actual values.

5.4. Determination of Long-Run Relationship Between Market Return and Sentiment Sub-Indices

We have analyzed our model for the determination of the long-term relationship between Indian stock market return and sentiment sub-indices using the ARDL bound test (Pesaran *et al.*, 2001). According to the results in Table 6, the calculated value of the f-statistic (Wald test) is equal to 10.11128, which shows the significant relationship among the return and sentiment sub-indices with optimal delay.

The F-statistic must be greater than the upper bound $I(1)$ for convergence to exist. Based on the test, the existence of an independent convergence vector between Indian stock market return and sentiment sub-indices was proven, indicating that there is a long-run relationship between return and sentiment sub-indices. Results are significant at all levels of significance (1%, 2.5%, 5%, and 10%).

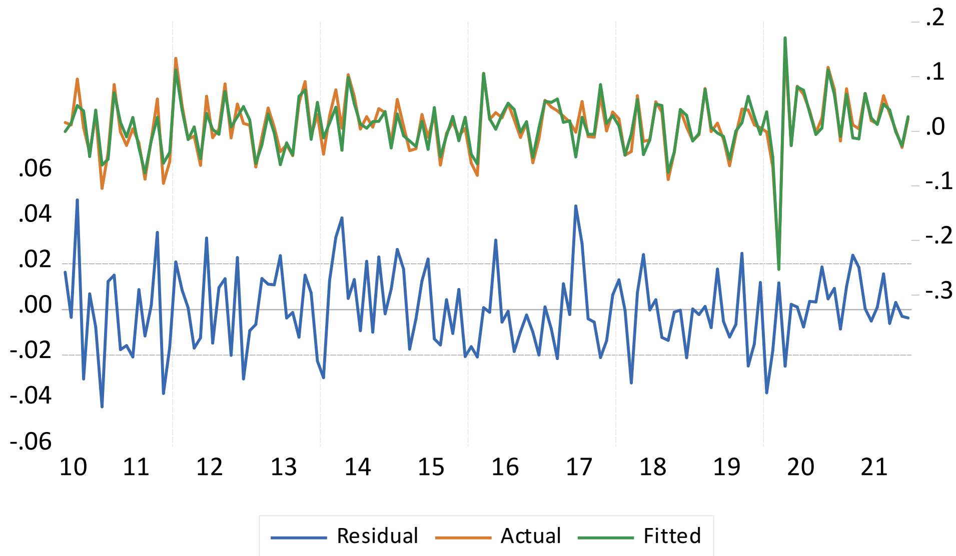

Figure 1: ARDL Model Graph

5.5. Long-Run Coefficients

Long-run coefficients are in Table 7, which show that sentiment sub-indices PC1, PC2, PC3, PC4, PC7, PC8, PC9, PC10, and PC11 have a significant long-run impact on the BSE500 return at a 5% level of significance. So far as PC5 and PC6 are concerned, they are statistically insignificant, which means there is no long-run linkage between these variables and the market return.

5.6. Error Correction Form

Now we run the error correction form test to check whether our model adjusts monotonically. The value of CointEq(-1) is -.860797 with a p value of 0.0000, which shows that the model will adjust monotonically. It implies that the system corrects its previous period at a speed of convergence of 86.08% per month. The adjustment time is very long, approximately one month (1/0.860797=1.16). Also, the t-statistic is very large, *i.e.*, -12.12700, which means that the coefficient is highly significant. The values of r^2 and adjusted r^2 are 0.945559 and 0.933997, which show that 94.5% and 93.4% of the deviation in the market return function are explained by regressors, *i.e.*, sentiment sub-indices.

5.7. Breusch-Godfrey Serial Correlation Lagrange Multiplier (LM) Test

We also checked our ARDL models for serial correlation through the Breusch–Godfrey Lagrange Multiplier (LM) Test. Results in Table 9 show that the null

Table 6: ARDL Model F Bound Test Results

Null Hypothesis: No levels relationship

Test Statistic	*Value*	*Signif.*	*I(0)*	*I(1)*
			Asymptotic: n=1000	
F-statistic	10.11128	10%	1.76	2.77
K	11	5%	1.98	3.04
		2.5%	2.18	3.28
		1%	2.41	3.61
Actual Sample Size	138		Finite Sample: n=80	
		10%	-1	-1
		5%	-1	-1
		1%	-1	-1

Source: Author's calculation based on results obtained in EViews 12

Table 7: Restricted Constant and No Trend

Levels Equation

Case 2: Restricted Constant and No Trend

Variable	*Coefficient*	*Std. Error*	*t-Statistic*	*Prob.*
PC1	-0.114410	0.015769	-7.255595	0.0000*
PC2	-0.017238	0.005534	-3.114667	0.0024*
PC3	0.026190	0.006435	4.069753	0.0001*
PC4	-0.017706	0.006991	-2.532794	0.0129*
PC7	0.026315	0.009742	2.701287	0.0081*
PC8	-0.033575	0.010183	-3.297202	0.0013*
PC9	-0.010816	0.004784	-2.261068	0.0259*
PC10	-0.047364	0.008469	-5.592637	0.0000*
PC11	-0.004704	0.002164	-2.173215	0.0321*
C	0.011363	0.002015	5.637957	0.0000*

* Significant at 5%

Source: Author's calculation based on results obtained in EViews 12

hypothesis of no serial correlation is accepted at a 5% level of significance. Thus, our ARDL model is free from serial correlation.

5.8. CUSUM and CUSUMQ Stability Test Results

The CUSUM and CUSUMQ stability test results of the model in Figures 2 and 3 show that the ARDL model lies well within the 5% significance limits shown by the red lines, and thus the model is stable.

However, a close look at the graphs gives some evidence of instability. The period of instability is from March 2020 to September 2020, and one of the possible reasons for this may be the period of the pandemic. Here, it is important to note that this instability affected not only India but the whole world. Another thing that is worth noting is that this instability quickly turned into stability.

Table 8: Error Correction Form

ECM Regression
Case 2: Restricted Constant and No Trend

Variable	*Coefficient*	*Std. Error*	*t-Statistic*	*Prob.*
D(BSE500RETURN(-1))	-0.142735	0.063262	-2.256257	0.0262*
D(BSE500RETURN(-2))	-0.389789	0.053496	-7.286273	0.0000*
D(PC1)	-0.050261	0.001954	-25.71950	0.0000*
D(PC1(-1))	0.022400	0.005859	3.823363	0.0002*
D(PC2)	-0.008182	0.001812	-4.514535	0.0000*
D(PC2(-2))	0.004458	0.001677	2.657992	0.0091*
D(PC3)	0.010271	0.001748	5.877356	0.0000*
D(PC3(-1))	-0.007318	0.001832	-3.994016	0.0001*
D(PC4)	-0.015937	0.002464	-6.469042	0.0000*
D(PC4(-2))	-0.003508	0.001647	-2.130540	0.0356*
D(PC5(-1))	-0.003813	0.001853	-2.057550	0.0422*
D(PC5(-2))	-0.004719	0.001699	-2.777367	0.0065*
D(PC7)	0.005513	0.001756	3.139462	0.0022*
D(PC7(-1))	-0.009971	0.002856	-3.491329	0.0007*
D(PC7(-2))	-0.005200	0.001813	-2.867449	0.0050*
D(PC8)	-0.011272	0.001805	-6.245496	0.0000*
D(PC8(-1))	0.006969	0.001640	4.248807	0.0000*
D(PC10)	-0.014404	0.001683	-8.558172	0.0000*
D(PC10(-1))	0.014245	0.002097	6.792934	0.0000*
CointEq(-1)*	-0.860797	0.070982	-12.12700	0.0000*
R-squared	0.945559			
Adjusted R-squared	0.933997			

*Significant at 5%
Source: Author's calculation based on PCA results obtained in EViews 12

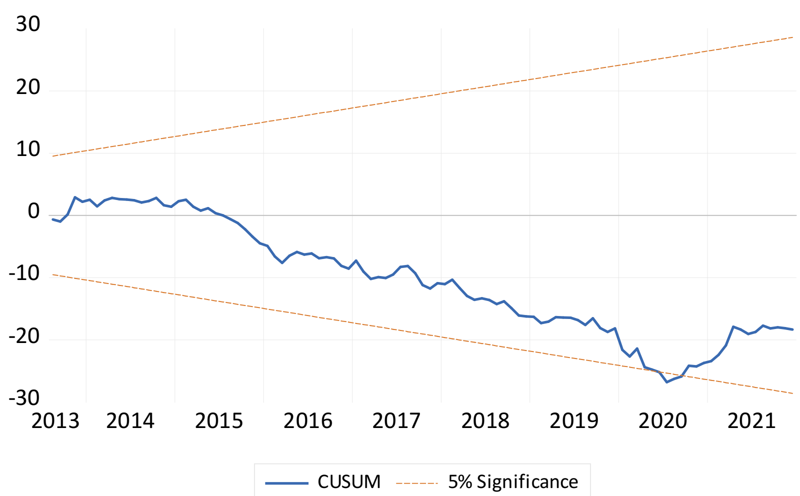

Figure 2: CUSUM Stability Test Results

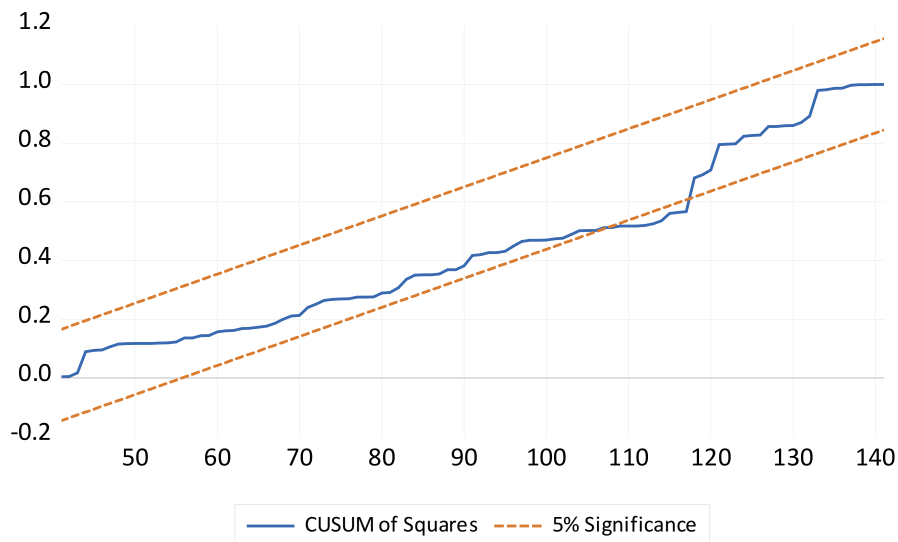

Figure 3: CUSUM of Squares Test Results

5.9. Testing the Robustness of the Model Using the Breusch-Pagan-Godfrey Heteroskedasticity Test

We have checked the model for robustness using the Breusch-Pagan-Godfrey heteroskedasticity test. The null hypothesis for this test is— "There is homoskedasticity in the model". The *p* value of the test results is 0.7133, which means that we accept the null hypothesis and conclude that there is no heteroskedasticity in the model (*see* Table 10).

Table 9: Breusch-Godfrey Serial Correlation Lagrange Multiplier (LM) Test

No serial correlation at up to two lags, according to null hypothesis			
F-statistic	0.469958	Prob. F (2,117)	0.6264
Obs*R-squared	1.297864	Prob. Chi-Square (1)	0.5226

Source: Author's own calculation

Table 10: Breusch-Pagan-Godfrey Heteroskedasticity Test Results

F-statistic	0.844042	Prob. F (36,101)	0.7133
Obs*R-squared	31.91524	Prob. Chi-Square (36)	0.6633

Source: Author's own calculation

6. Conclusion

We have examined the interesting issue of whether sentiment sub-indices influence the returns of the Indian stock market. By applying the Auto Regressive

Distributed Lag (ARDL) model to sentiment sub-indices and stock market return (S & P BSE 500) monthly data for the period from April 2010 to December 2021, we tested for a long-run dynamic relationship. We identified 32 proxies for sentiment based on an extensive literature review and data availability, and then selected 23 proxies based on inter-correlations. Then these 23 proxies were reduced to 11 sentiment sub-indices with the use of principal component analysis, *viz.*, "Market and Economic Variables", "Market Ratios", "Advance-Decline Ratio and High-Low Index", "Price to Book Value Ratio and Liquidity in Economy", "Oil Price and Industrial Production Index", "Put-Call Ratio", "Ratio of Equity in Total Issues and Total Number of Issues", "Buy-Sell Imbalance and Foreign Direct Investment", "Trading-Volume Ratio", "Extra Return on Market Portfolio" and "Term-Spread". The most representative stock market index, the S&P BSE 500, has been used to calculate market return.

We have got some new insights. The market return is related to its own lagged values. All the sentiment sub-indices (contemporaneous values) are related to market return except "Oil Price and Industrial Production Index", "Put-Call Ratio" and "Trading-Volume Ratio". The market return has a significant relationship with lagged values of "Market and Economic Variables", "Market Ratios", "Advance-Decline Ratio and High-Low Index", "Price to Book Value Ratio and Liquidity in Economy", "Oil Price and Industrial Production Index", "Ratio of Equity in Total Issues and Total Number of Issues", "Buy-Sell Imbalance and Foreign Direct Investment", "Trading Volume Ratio" and "Extra Return on Market Portfolio".

It is interesting to note that we found no relationship between contemporaneous values of the "Put-Call Ratio" and the market return, which have been considered proxies for investor sentiment by some studies (see Bandopadhyaya & Jones (2008); Dash & Mahakud (2013b)).

Thus, based on the results, the hypothesis of this study, indicating the long-run relation between sentiment sub-indices and market return, cannot be refuted. After determining the order of VAR based on Akaike's information criterion, we have estimated the vector error correction model. The obtained ECM coefficient of -0.860797 shows that the speed of deviation adjustment from short-term to long-term is very high. One of the possible explanations for this may be that Indian investors are not fearful and don't like to wait a long time for the market to revive before starting to invest again. Our model is robust in terms of serial correlation and heteroskedasticity.

Results are useful to policymakers, regulators, and the investor community. Policymakers and regulators should watch out for the impact of fluctuations in different sentiment sub-indices. Investors can search for the presence of exploitable arbitrage opportunities in the Indian stock market to earn above-normal returns on the basis of sentiment sub-indices but not on the basis of the "Put-Call Ratio" sub-index.

Now, these findings pose more questions, like whether there is any difference between the prediction power of investor sentiment and macroeconomic variables; or if these sub-indices can be used to predict the industry return; or if they can be used to predict volatility.

Also, we wish to analyze the effect of our index on market return in the context of developing foreign financial markets such as the BRICS countries. However, in this process, some elements of the index may have to be removed and some new elements may have to be added, depending on the availability or non-availability of the data.

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