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Impact of Investor Sentiment on Portfolio Return: An ARDL Approach

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ABSTRACT: This paper pioneers an investigation into the intricate relationship between investor sentiment and BSE Sensex returns from January 2010 to December 2021. Employing 32 market and macroeconomic variables as proxies for investor sentiment, we utilized principal component analysis to distill these variables into 11 principal components with eigenvalues exceeding 1, thus creating investor sentiment sub-indices. Utilizing the Auto-Regressive Distributive Lag method, we aimed to elucidate the impact of sentiment on portfolio returns.

Our findings reveal a significantly positive impact of sentiment on portfolio returns throughout the study period. These results hold valuable implications for various stakeholders in the Indian stock market, including retail investors, policymakers, and decisionmakers. Retail investors can leverage these findings as guidance for their decision-making processes, gaining insight into the relationship between sentiment and portfolio returns. Additionally, policymakers and decisionmakers can utilize these insights to inform market strategies and risk management practices.

By delving into the relationship between sentiment and portfolio returns in the Indian stock market, this study contributes significantly to the existing literature. It sheds light on a previously unexplored aspect of market dynamics, offering valuable insights for further research and practical applications in the realm of investor sentiment and market behavior.

KEYWORDS: ARDL, Investor Sentiment, Portfolio Return, Principal Component Analysis

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1. INTRODUCTION

Investor sentiment, though elusive to define precisely, has garnered significant attention among scholars. Keynes (1936) was among the first to underscore its importance, asserting that investor sentiment influences future asset profits. He posited that investors are driven by "animal spirits," shaping their investment decisions. Classical finance theory contends that markets are primarily inhabited by rational actors whose competition leads to equilibrium pricing based on fundamental values derived from discounted cash flows. However, irrational investors, often referred to as noise traders, may incur losses and eventually exit the market (Black, 1986). Stocks resistant to arbitrage tend to exhibit subjective pricing influenced by speculation (Baker & Wurgler, 2006), as theorized by De Long *et al.* (1990).

While recognizing sentiment's significance, its measurement and impact on stock prices have posed ongoing challenges. Keynes (1936) stressed the importance of understanding investors' concerns and emotions to evaluate investment prospects. It's commonly held that high (low) sentiment drives asset prices above (below) fundamental values, yielding higher (lower) returns (Sehgal *et al.*, 2009). However, measuring sentiment remains elusive and often relies on proxies due to its intangible nature (Schmeling, 2009). Baker & Wurgler (2004a, 2004b) proposed several proxies for sentiment measurement, with surveys being a potential method to glean insights. The literature offers no constraint on the number of proxies used, with different studies employing varying sets to establish the sentiment-return relationship.

Numerous studies have documented this link, albeit with varying degrees of intensity contingent upon the proxies and methodologies employed. In our study, we endeavor to comprehensively measure sentiment by incorporating multiple proxies, subsequently distilled into sentiment sub-indices through principal component analysis. We aim to analyze the relationship between sentiment and portfolio returns across diverse economic and market conditions.

Our findings unveil a statistically significant positive relationship between sentiment (sub-indices) and portfolio returns, aligning with existing literature. This paper contributes to scholarship by exhaustively identifying sentiment proxies, constructing sentiment sub-indices, and scrutinizing the sentiment-portfolio return nexus. Our primary objective is to investigate the impact of investor sentiment on portfolio returns.

The remainder of this paper unfolds as follows: Section 2 reviews pertinent literature, while Section 3 delineates our data and methodology. In Section 4, we present empirical evidence alongside an analysis of the sentiment-portfolio return relationship. Finally, Section 5 offers conclusions, policy implications, and limitations.

2. REVIEW OF LITERATURE

Investor sentiment, often characterized as a belief rooted in perception rather than evidence, has long captivated scholars. Keynes (1936) likened it to the "animal spirits" driving human behavior in financial markets. This view was echoed by Zweig (1973), who framed sentiment as integral to investors' comparative assessments of their investments. Supporting this notion, Lee *et al.* (2002) argued that melding sentiment with economic fundamentals alone falls short in predicting market returns. A salient dimension of sentiment is investors' inclination to engage in speculative behavior (Baker & Wurgler, 2006), a sentiment aspect affirmed by Smidt (1968) and Baker & Wurgler (2007).

Sehgal *et al.* (2010) characterized sentiment as a driver of investor behavior influencing stock market dynamics, emphasizing the emotions and confidence exhibited by investors during market interactions (Bennet, 2011; Bennet & Selvam, 2011). Numerous studies have delved into the sentiment-return relationship, employing various proxies and methodologies to gauge sentiment's impact on market behavior.

Whaley (2009), Simon & Wiggins III (2001), and Giot (2005) utilized the VIX™ as a sentiment proxy, demonstrating its positive effect on market returns. Similarly, Lee *et al.* (2002) and Rawlings *et al.* (1998) leveraged intelligence sentiment surveys and consumer confidence indices, respectively, revealing significant sentiment-return relationships. However, Brown & Cliff (2004) cautioned against relying solely on survey methods, advocating for direct measurement approaches. Baker & Wurgler (2006, 2007) pioneered a composite sentiment index using principal components, corroborating a significant sentiment-return relationship.

Schmeling (2009) expanded this analysis internationally, finding consistent sentiment-return

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relationships across 18 countries, a conclusion echoed by Baker & Wurgler (2012) across six countries. Concetto & Ravazzolo (2019) developed sentiment indices for the US and EU markets, highlighting sentiment's impact on market returns, albeit with varying predictive power.

In India, Sehgal *et al.* (2009) laid the groundwork by identifying sentiment proxies via survey methods and constructing sentiment indices. Subsequent studies, like Liu *et al.* (2011) and Yoshinaga & Castro Junior (2012), explored sentiment's role in extreme stock market conditions. Ahmed & Ullah (2013) and Naik & Padhi (2016) examined sentiment's impact on market returns and volatility in specific contexts, confirming its significance.

Aggarwal (2017), Yang & Hasuike (2017), and Zhou (2018) further delineated sentiment's influence on market dynamics, while Pandey & Sehgal (2019) and Gupta & Maurya (2021) developed composite sentiment indices, enhancing market return predictability. Despite these advancements, research in India remains nascent, predominantly focusing on sentiment's relationship with market return and volatility, often with limited sentiment proxies.

Unlike previous studies, our research aims to comprehensively measure sentiment using diverse proxies and assess its impact on portfolio returns. By filling this gap, we seek to advance understanding of sentiment's role in shaping portfolio returns, contributing to the broader literature on investor behavior and market dynamics.

3. DATA AND METHODOLOGY

The research utilized a dataset comprising 141 monthly observations spanning from April 2010 to December 2021, encompassing 32 proxies sourced from diverse platforms including the BSE, NSE, RBI, SEBI, indexmundi.com, IMF, CSO, and Department for Promotion of Industry and Internal Trade websites. Data underwent rigorous refinement and standardization procedures. To ensure stationarity, unit root tests (ADF and PP) were employed, followed by the application of first-order differencing to render the series stationary.

Subsequently, the 32 proxies were subjected to correlation analysis using EViews 12, leading to the removal of highly correlated variables and those not referenced in existing literature, resulting in a refined set of 23 variables. Principal component analysis (PCA) was then applied to these variables, yielding 11 principal components explaining 78.251% of the total variance. Varimax rotation and Kaiser criterion (Kaiser, 1960) were utilized to extract these components, which were designated as sentiment sub-indices. The high internal consistency of these sub-indices was confirmed by Cronbach's alpha coefficient of 0.857.

Moreover, the Kaiser-Meyer Olkin (KMO) measure, calculated at 0.835, affirmed the suitability of principal component analysis for the dataset, indicating that the variables' inter-correlations were adequate for PCA. To enhance interpretability, the sentiment sub-indices were assigned meaningful labels. Details of the 11 final sentiment sub-indices and their respective eigenvalues are presented in Table 1. Furthermore, the selection of individual proxies contributing to each principal component was based on their maximum factor loadings, as delineated in Table 2.

The study used a total of 141 monthly observations on 32 proxies from April 2010 to December 2021. The data was collected from various sources such as the BSE website, NSE website, RBI website, SEBI website, indexmundi.com, IMF website, CSO website, and Department for Promotion of Industry and Internal Trade website. The data was subject to refinement and standardization. Data was tested for stationarity using unit root test (ADF and PP) and first-order difference of all the data series was taken to make the series stationary. Data on 32 proxies was then put in EViews 12 and a correlation matrix was prepared. Highly correlated variables and variables not mentioned in the literature were removed and we were left with 23 variables. On these 23 variables, we applied the principal component analysis and the first 11 principal components explaining 78.251% of the total variance, were extracted using varimax rotation and Kaiser criterion (Kaiser, 1960), and these were termed as sentiment sub-indices. Cronbach's alpha came out to be 0.857 showing good internal consistency. The Kaiser-Meyer Olkin (KMO) came out to be 0.835 showing that principal component analysis of the variables is a good idea. These sentiment sub-indices were given meaningful names for a better understanding. The 11 final sentiment sub-indices and their eigenvalues are given in Table 1. The individual proxies that contributed to the particular principal component were selected based on the maximum factor loading of each proxy. Maximum Factor Loadings are in Table 2.

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The construction of a portfolio for analytical purposes necessitates careful consideration of the underlying investments. In this study, the BSE Sensex was chosen as the portfolio benchmark due to its representation of 30 stocks from reputable Indian companies listed on the Bombay Stock Exchange. Data about the constituents of the BSE Sensex was meticulously sourced from the BSE website, ensuring the inclusion of financially robust entities within the portfolio.

Drawing from the methodological framework introduced by Pesaran *et al.* (1996), we adopted the Auto-Regressive Distributed Lag (ARDL) approach to examine the long-term relationship between portfolio return and sentiment sub-indices in the Indian stock market. This analytical methodology, consistent with the framework proposed by Tripathi and Kumar (2015a, 2015b), provides a robust foundation for our research endeavors.

Utilizing Eviews 12 software, we leveraged the ARDL model to determine the optimal lag length, thus facilitating a comprehensive analysis. Defined as an auto-regressive distributed lag model, this approach enables us to explore the intricate dynamics between portfolio 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 sentiment variables and portfolio returns over time. An auto-regressive distributed lag model is defined as follows—$ARDL\ (1,1) model$:

$$y_t = \mu + \alpha_1 y_{t-1} + \beta_0 x_t + \beta_1 x_{t-1} + u_t \dots\dots\dots (1)$$

Where,

y_t =Stationary variable

x_t =Stationary variable

u_t =White noise

The primary hypotheses for our study are as follows:

H_0: There is no long-run relationship between portfolio return and sentiment sub-indices.

H_1: There is a long-run relationship between portfolio return and sentiment sub-indices.

These hypotheses serve as the cornerstone of our investigation into the potential linkages between portfolio return and sentiment sub-indices. Through rigorous analysis and empirical testing, we seek to either accept or refute these hypotheses, thereby shedding light on the existence and nature of any long-term associations between portfolio performance and sentiment indicators.

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 both the Augmented Dickey-Fuller (ADF) test and the Phillips Perron test on our sentiment sub-indices (Taghizadeh and Ahmadi, 2019; Onatski & Wang, 2021).

The results revealed that all sentiment sub-indices exhibited stationarity at the 1% significance level, both at the level and after taking the first difference. This indicates that the original variables were stationary at their first difference, as illustrated in Table 3 below. Thus, our data meets the necessary stationarity criteria for conducting further econometric analyses, ensuring the reliability and validity of our findings.

4. RESULT AND DISCUSSION

Tables 4, 5, and 6 present the results of our analysis. The findings indicate a significant relationship between the portfolio return and six variables: SENSEXRETURN, PC1, PC2, PC3, PC4, PC8, and PC10. Notably, the coefficient of determination (r^2) is calculated to be 0.816574, exceeding the threshold of 0.6. This suggests that the model merits attention due to its substantial explanatory power. Additionally, the adjusted r^2 value, standing at 0.785219, further supports the model's credibility by accounting for the number of predictors in the model.

The F-statistic is significant at the 5% level, indicating that the coefficients are unequal. Our results demonstrate that portfolio return is significantly influenced by itself, PC1, PC2, PC3, PC4, PC8, and PC10. Specifically, we observe a significant negative relationship between portfolio return and the lagged values of PC1, PC2, PC4, PC8, and PC10, while a positive relationship exists with its own lagged values and PC3. Conversely, there is no evident association between PC5, PC6, PC7, PC9, PC11, and portfolio return.

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The Durbin-Watson statistic is computed as 2.110425, suggesting the absence of autocorrelation in the model (Durbin & Watson, 1971).

Regarding the individual sentiment sub-indices, those with a p-value less than 0.05 *viz*. PC1, PC2, PC3, PC4, PC8, and PC10—reject the null hypotheses (H_{0S1}, H_{0S2}, H_{0S3}, H_{0S4}, H_{0S8}, and H_{0S10}), signifying their significant impact on portfolio return. Conversely, PC5, PC6, PC7, PC9, and PC11, with p-values exceeding 0.05, fail to reject the null hypotheses (H_{0S5}, H_{0S6}, H_{0S7}, H_{0S9}, and H_{0S11}), indicating their lack of significant impact on portfolio return. Thus, these sentiment sub-indices are deemed irrelevant in explaining portfolio return.

To ensure the robustness of our model, 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 depicts that the fitted values of the BSE Sensex closely align with the actual values, affirming the reliability of our model.

Table 5 presents the results of the variance inflation factor (VIF), which indicates the absence of multicollinearity in the data. The entries in the table demonstrate that there is no significant correlation between the predictors, suggesting that the variance of the variables is not inflated. This absence of multicollinearity enhances the reliability of our model and ensures the validity of our findings.

The results of the Breusch-Godfrey Serial Correlation LM test, as shown in Table 5, indicate that the probability values (0.6407 and 0.5695) exceed the significance level of 0.05. This suggests that we cannot reject the null hypothesis, which indicates no serial correlation in the model. Therefore, we accept the null hypothesis, concluding that the model does not exhibit issues of serial correlation.

Similarly, the outcomes of the Breusch-Pagan-Godfrey heteroskedasticity test, also depicted in Table 5, demonstrate probability values (0.5430, 0.5189, and 0.9477) that surpass the 0.05 significance level. This suggests an inability to reject the null hypothesis of homoscedasticity. Consequently, we accept the null hypothesis, confirming that the model maintains equal variance (homoscedastic).

Furthermore, the Ramsey RESET test confirms the absence of specification errors in the model. This ensures that no relevant variables were overlooked, the model's functional form is correct, and no serial correlation exists between the independent variables and the disturbance term.

Overall, the examination of serial correlation and heteroskedasticity, as detailed in Table 6, affirms the validity of the model, as it is free from these issues. The presence of serial correlation and heteroskedasticity can undermine the validity of a model.

The stability of the model is evaluated through the Cumulative Sum of Recursive Residuals (CUSUM), Cumulative Sum of Squares of Recursive Residuals (CUSUMSQ), and Inverse Root of AR Characteristic polynomial tests. In Figures 2 and 3, the blue line remains within the upper and lower limits, delineated by the two red lines. This observation suggests that the model retains stability when estimated at lag 3.

Likewise, in the Inverse Root graph illustrated in Figure 4, none of the roots extend beyond the unit circle (modulus). This indicates that all modulus values of the complex roots are below 1. Therefore, it can be inferred that the model at lag 3 satisfies the stability criterion.

The model's stability is assessed using Cumulative Sum of Recursive Residuals (CUSUM), Cumulative Sum of Squares of Recursive Residuals (CUSUMSQ), and Inverse Root of AR Characteristic polynomial tests. In Figures 2 and 3, the blue line falls within the upper and lower limits represented by the two red lines. This observation indicates that the model remains stable when estimated at lag 3.

We performed an analysis of our model to determine the long-term relationship between Indian stock portfolio returns and sentiment sub-indices using the ARDL bound test (Pesaran *et al.*, 2001).

In this test, if the F-statistic surpasses the upper bound value, it suggests the presence of cointegration. Conversely, if the F-statistic falls within the upper and lower bound values, the result is inconclusive. A F-statistic lower than the lower bound value indicates no cointegration.

According to the results presented in Table 7, the calculated value of the F-statistic (Wald test) is 14.28288. This suggests a significant relationship between returns and sentiment sub-indices with an optimal delay.

To confirm the presence of convergence, the F-statistic needs to exceed the upper bound $I(1)$. Our test outcomes

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validate the existence of an independent convergence vector between Indian stock portfolio returns and sentiment sub-indices. This substantiates a long-run relationship between returns and sentiment sub-indices. Remarkably, the results demonstrate significance across all levels (1%, 2.5%, 5%, and 10%) of significance (*see* Table 8).

The long-run coefficients given in Table 9 elucidate that sentiment sub-indices PC1, PC2, PC3, PC4, PC8, and PC10 affect portfolio return in the long-term at a significance level of 5%. Conversely, PC5, PC6, PC7, PC9, and PC11 exhibit statistical insignificance, signifying no long-term correlation of these variables with portfolio return.

We proceeded to conduct the error correction form test to evaluate the monotonic adjustment of our model. As depicted in Table 10, the estimation of short-run coefficients for portfolio returns alongside its structural variables and the $CointEq(-1)$ value were provided. The $CointEq(-1)$ value stands at -0.730249, with a p-value of 0.0000, indicating that the model adjusts monotonically. This suggests that the system corrects its previous period at a convergence speed of 73.02% per month. The duration for adjustment is notably high, approximately 1 month (1/0.730249=1.37), indicating a swift return to equilibrium.

Moreover, the t-statistic registers a substantial value of -12.43784, indicating the high significance of the coefficient. Additionally, the values of r^2 and adjusted r^2 are 0.916693 and 0.907959, respectively. These figures imply that 91.7% and 90.8% of the deviation in the portfolio return function is explained by the regressors, namely sentiment sub-indices.

The Durbin-Watson statistic is a measure used to detect the presence of autocorrelation in the residuals of a regression analysis. In our model, the calculated Durbin-Watson value is 2.110425, indicating that there is no autocorrelation among the variables. This value falls within the acceptable range of 0 to 4, suggesting that the residuals do not exhibit significant serial correlation. Therefore, we can conclude that our model satisfies the assumption of no autocorrelation in the residuals.

5. ANALYSIS AND INTERPRETATION

We examined the influence of sentiment sub-indices on portfolio returns using the Auto Regressive Distributed Lag (ARDL) model applied to sentiment proxies and the monthly portfolio return (S&P BSE SENSEX) spanning from April 2010 to December 2021. Our objective was to unveil long-term dynamic relationships.

Drawing from an exhaustive literature review and meticulous data assessment, we initially identified 32 sentiment proxies, which were subsequently refined to 23 based on their inter-correlations. Employing principal component analysis, we condensed these proxies into 11 sentiment sub-indices, including "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 Index of Industrial Production," "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 S&P BSE SENSEX served as the primary representative stock market index for calculating portfolio returns.

Our analysis unveiled intriguing findings. Notably, we observed a relationship between portfolio returns and their lagged values which is in line with Rohilla & Tripathi (2022). Moreover, all sentiment sub-indices, except for "Oil Price and Index of Industrial Production," "Put-Call Ratio," "Ratio of Equity in Total Issues and Total Number of Issues," "Trading-Volume Ratio," and "Term-Spread," displayed contemporaneous relationships with portfolio returns.

Of particular interest was the absence of a relationship between the "Put-Call Ratio" and portfolio return, contradicting its previous designation as a sentiment proxy by Bandopadhyaya & Jones (2008) and Dash & Mahakud (2013b). The analysis did not refute the hypothesis of a long-term relationship between sentiment sub-indices and portfolio returns.

Subsequently, we determined the order of VAR using Akaike's information criterion and estimated the vector error correction model. The obtained ECM coefficient of -0.730249 suggests a rapid adjustment speed from short-term to long-run, potentially indicating Indian investors' readiness to resume investment without prolonged waiting periods for market revival.

Our model demonstrates robustness concerning serial correlation and heteroskedasticity, providing valuable insights for policymakers, regulators, and the investor

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community. Policymakers and regulators should monitor the impact of fluctuations in different sentiment sub-indices, while investors can explore arbitrage opportunities based on these indices, excluding “Oil Price and Index of Industrial Production,” “Put-Call Ratio,” “Ratio of Equity in Total Issues and Total Number of Issues,” “Trading-Volume Ratio,” and “Term-Spread.”

These intriguing findings prompt additional inquiries:

- Are sentiment sub-indices equally predictive of portfolio returns across diverse market conditions?
- Do these sub-indices forecast portfolio returns similarly amidst varying economic circumstances?
- Is there a discernible disparity in predictive capability between investor sentiment and macroeconomic variables?
- Can these sub-indices accurately predict industry returns or volatility?

6. CONCLUSION

In this study, we delve into the complex relationship between sentiment sub-indices and portfolio returns, aiming to offer valuable insights into the dynamics of the Indian stock market. Employing the Auto Regressive Distributed Lag (ARDL) model, we examine the influence of sentiment sub-indices on monthly portfolio returns, specifically focusing on the S&P BSE SENSEX index from April 2010 to December 2021.

Through a comprehensive literature review and meticulous data analysis, we curated 32 sentiment proxies, which were refined to 23 based on inter-correlations. Utilizing principal component analysis, we condensed these proxies into 11 sentiment sub-indices, covering diverse aspects of market sentiment, including performance ratios, trading indicators, and economic risk premiums.

Our findings uncover compelling insights into the relationship between sentiment sub-indices and portfolio returns. We observed a robust relationship between portfolio returns and lagged values, indicating the enduring impact of investor sentiment on market performance. Additionally, our analysis revealed contemporaneous relationships between portfolio returns and most sentiment sub-indices, emphasizing the significance of investor sentiment in driving market outcomes.

Of particular interest was the absence of a relationship between certain sentiment sub-indices, such as the “Put-Call Ratio” and “Oil Price and Index of Industrial Production,” with portfolio returns. These findings echo observations made in our previous research, highlighting the nuanced nature of sentiment-driven market dynamics.

Our results underscore the importance of integrating sentiment analysis into market forecasting and investment strategies. Policymakers, regulators, and investors can benefit from a deeper understanding of market sentiment, informing timely decision-making and risk management practices. Furthermore, our findings underscore the need for further exploration into the predictive power of sentiment sub-indices under varying market and economic conditions, as well as their implications for industry returns and market volatility.

This study contributes to the expanding literature on market sentiment and portfolio returns, shedding light on the intricate interplay between investor sentiment and market performance in the Indian stock market context. Moving forward, we advocate for continued research in this area, focusing on refining sentiment analysis methodologies and exploring the broader implications of sentiment-driven market dynamics.

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Table 1: Final Sentiment Proxies, Eigen Values and Variance Explained

Principal component	Name of the principal component	Eigenvalue	Proportion variance	Cumulative
PC1	Market and Economic Variables	3.757	16.336%	16.336%
PC2	Market Ratios	2.826	12.287%	28.623%
PC3	Advance-Decline Ratio and High-Low Index	1.757	8.263%	36.887%
PC4	Price to Book Value Ratio and Liquidity in Economy	1.901	6.755%	43.641%
PC5	Oil Price and Industrial Production Index	1.554	6.234%	49.876%
PC6	Put-Call Ratio	1.434	5.837%	55.713%
PC7	Ratio of Equity in Total Issues and Total Number of Issues	1.343	5.126%	60.839%
PC8	Buy-Sell Imbalance and Foreign Direct Investment	1.179	4.820%	65.659%
PC9	Trading-Volume Ratio	1.109	4.652%	70.311%
PC10	Extra Return on Market Portfolio	1.070	4.225%	74.535%
PC11	Term-Spread	.972	3.717%	78.252%

(Source: Author's own calculations in EViews 12)

Table 2: Maximum Factor Loadings

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
IIP	.231	.361	-.112	-.280	.636	.104	.059	-.038	.063	.059	.165

(Source: Author's own compilation in EViews 12)

Table 3: Augmented Dickey-Fuller Test results, Phillips Perron Test results

Sentiment Sub-Indices	At Level		At Level	
	Dickey-Fuller Test (ADF)		Phillips Perron Test (PP)	
	t-statistic	Probability	t-statistic	Probability
PC1	-13.30413	0.000	-27.91299	0.0001
PC2	-11.33955	0.000	-11.40130	0.0000
PC3	-17.22338	0.000	-18.45608	0.0000
PC4	-16.94444	0.000	-11.76824	0.0000
PC5	-10.27386	0.000	-10.00482	0.0000
PC6	-10.65050	0.000	-22.25171	0.0000
PC7	-9.636241	0.000	-49.02464	0.0001
PC8	-11.46551	0.000	-28.43231	0.0001

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PC9	-13.56784	0.000	-26.25296	0.0000
PC10	-12.65277	0.000	-25.60852	0.0000
PC11	-8.991572	0.000	-72.87167	0.0001

(Source: Author's own compilation in EViews 12)

Table 4: ARDL Model Summary-BSE Sensex Percentage Return and Sentiment

Dependent Variable: SENSEXRETURN				
Method: ARDL				
Sample (adjusted): 2010M07 2021M12				
Included observations: 138 after adjustments				
Maximum dependent lags: 3 (Automatic selection)				
Model selection method: Akaike info criterion (AIC)				
Dynamic regressors (3 lags, automatic): PC1 PC2 PC3 PC4 PC5 PC6 PC7 PC8 PC9 PC10 PC11				
Fixed regressors: C				
Number of models evaluated: 12288				
Selected Model: ARDL (3, 2, 1, 0, 0, 2, 2)				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.*/****
SENSEXRETURN(-3)	0.311959	0.058901	5.296344	0.0000
PC1	-0.046299	0.002704	-17.12305	0.0000
PC1(-1)	-0.018064	0.004882	-3.700551	0.0003
PC1(-2)	-0.016530	0.004575	-3.613158	0.0004
PC2(-1)	-0.004947	0.002334	-2.119552	0.0362
PC3	0.008843	0.002416	3.660936	0.0004
PC4	-0.016497	0.003528	-4.675974	0.0000
PC4(-3)	0.004148	0.002124	1.952792	0.0532
PC8	-0.009535	0.002716	-3.510314	0.0006
PC8(-1)	-0.010487	0.003256	-3.220524	0.0017
PC8(-2)	-0.009337	0.003241	-2.880592	0.0047
PC10(-2)	-0.008532	0.002742	-3.111433	0.0023
C	0.008121	0.002380	3.411592	0.0009
R-squared	0.816574	**Mean dependent variable**		0.009908
Adjusted R-squared	0.785219	**S.D. dependent variable**		0.049519
S.E. of regression	0.022950	**Akaike info criterion**		-4.571773
Sum squared residual	0.061622	**Schwarz criterion**		-4.126321
Log-likelihood	336.4523	**Hannan-Quinn information criterion**		-4.390752
F-statistic	26.04299	**Durbin-Watson statistic**		2.110425
Prob(F-statistic)	0.000000			

(Source: Author's own compilation in EViews 12)

* $\boldsymbol{p}$ values and any subsequent tests do not account for model selection, **Significant at 5%, ***Significant at 20%

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 both variables whether *I* (0) or *I* (1). (*see* Pesaran *et al.* (2001) and Omar *et al.* (2015) for details).

Table 5: Variance Inflation Factors

Variance Inflation Factors			
Sample: 2010M04 2021M12			
Included observations: 138			
Variable	**Coefficient Variance**	**Uncentered VIF**	**Centered VIF**
SENSEXRETURN(-3)	0.003798	2.595548	2.491582
PC1	7.28E-06	1.923620	1.923576
PC1(-1)	2.51E-05	1.803920	1.803549
PC1(-2)	2.43E-05	1.581396	1.580952
PC2(-1)	6.68E-06	1.797291	1.797207
PC3	5.81E-06	1.482642	1.482609
PC4	1.33E-05	1.620159	1.612315
PC4(-3)	4.51E-06	1.191359	1.191294
PC8	7.48E-06	2.037861	2.037857

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PC8(-1)	9.62E-06	2.612285	2.612258
PC8(-2)	9.22E-06	2.500927	2.500927
PC10(-2)	7.48E-06	1.993291	1.992939
C	4.83E-06	1.299018	NA

(Source: Author's own compilation in EViews 12)

Table 6: Results of Serial Correlation and Heteroskedasticity Test

Breusch-Godfrey Serial Correlation Lagrange Multiplier (LM) Test			
Null hypothesis: No serial correlation at up to 3 lags			
F-statistic	0.562763	**Prob. F(2,127)**	0.6407
Obs*R-squared	2.013893	**Prob. Chi-Square(2)**	0.5695
Heteroskedasticity Test: ARCH			
F-statistic	0.936584	**Prob. F(24,113)**	0.5430
Obs*R-squared	19.04472	**Prob. Chi-Square(24)**	0.5189
Scaled explained SS	10.94146	**Prob. Chi-Square(24)**	0.9477
Ramsey RESET Test			
	Value	**Df**	**Prob.**
t-statistic	1.226813	116	0.2224
F-statistic	1.505069	(1, 116)	0.2224

(Source: Author's own compilation in EViews 12)

Table 7: Bound Test Results

F-Bounds Test		**Null Hypothesis:** No levels relationship		
Test Statistic	**Value**	**Signif.**	**I(0)**	**I(1)**
			Asymptotic: n=1000	
F-statistic	14.28288	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 own compilation in EViews 12)

Table 8: Error Correction Model Results

F-Bounds Test		**Null Hypothesis:** No levels relationship		
Test Statistic	**Value**	**Signif.**	**I(0)**	**I(1)**
F-statistic	18.24586	10%	1.99	2.94
K	6	5%	2.27	3.28
		2.5%	2.55	3.61
		1%	2.88	3.99

(Source: Author's own compilation in EViews 12)

Table 9: Restricted Constant and No Trend

Levels Equation				
Case 2: Restricted Constant and No Trend				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
PC1	-0.110775	0.018189	-6.090067	0.0000
PC2	-0.010389	0.004765	-2.180359	0.0312
PC3	0.012110	0.003960	3.057695	0.0028
PC4	-0.018391	0.008853	-2.077488	0.0399
PC8	-0.043643	0.014865	-2.935997	0.0040
PC10	-0.022126	0.008594	-2.574567	0.0113
C	0.011121	0.002711	4.101938	0.0001

*** Significant at 5%**

(Source: Author's own compilation)

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Table 10: Error Correction Form

ECM Regression				
Case 2: Restricted Constant and No Trend				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
D(SENSEXRETURN(-1))	-0.246889	0.054710	-4.512715	0.0000
D(SENSEXRETURN(-2))	-0.311959	0.044459	-7.016751	0.0000
D(PC1)	-0.046299	0.002024	-22.87321	0.0000
D(PC1(-1))	0.016530	0.003868	4.273445	0.0000
D(PC2)	-0.002639	0.001602	-1.647222	0.1022
D(PC4)	-0.016497	0.002575	-6.405651	0.0000
D(PC4(-1))	-0.002292	0.002690	-0.851817	0.3961
D(PC4(-2))	-0.004148	0.001783	-2.325754	0.0218
D(PC8)	-0.009535	0.001787	-5.336124	0.0000
D(PC8(-1))	0.011848	0.002624	4.516154	0.0000
D(PC8(-2))	0.002511	0.001820	1.379971	0.1702
D(PC10)	-0.003408	0.001724	-1.976517	0.0504
D(PC10(-1))	0.008532	0.001881	4.536656	0.0000
CointEq(-1)*	-0.730249	0.058712	-12.43784	0.0000
R-squared	0.916693	**Mean dependent variable**		-0.000172
Adjusted R-squared	0.907959	**S.D. dependent variable**		0.073479
S.E. of regression	0.022292	**Akaike info criterion**		-4.673222
Sum squared residual	0.061622	**Schwarz criterion**		-4.376254
Log likelihood	336.4523	**Hannan-Quinn criterion**		-4.552542
Durbin-Watson statistic	2.110425			

***Significant at 5%**

(Source: Author’s own compilation)

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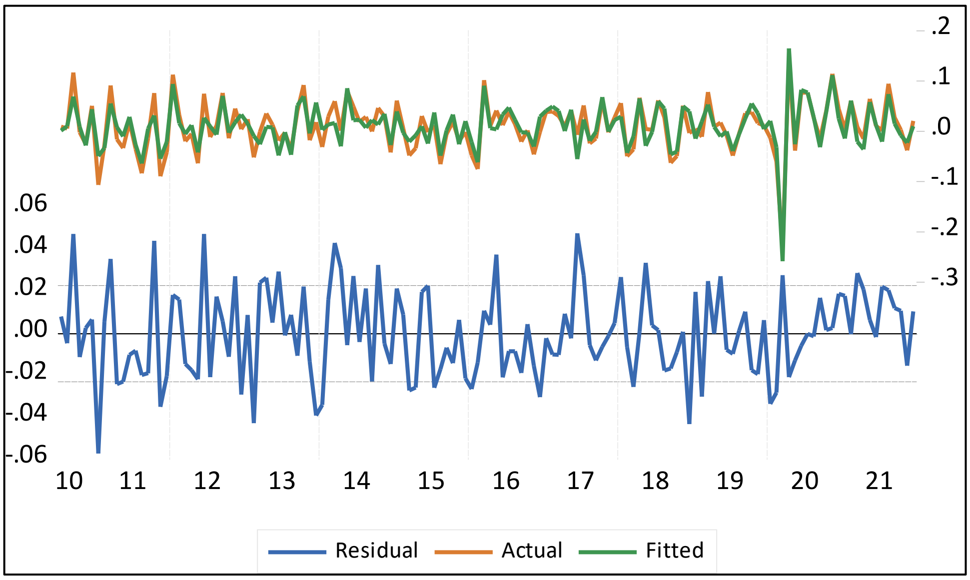

Figure 1: Residual, Fitted, and Actual Values

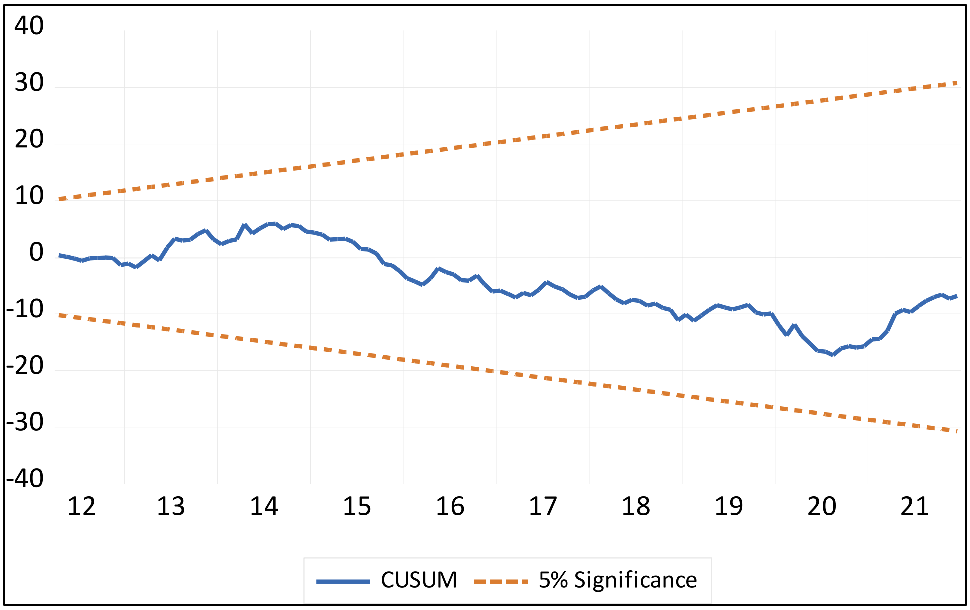

Figure 2: CUSUM Test Results

DOI: https://doi.org/10.48001/veethika.2024.10.02.004

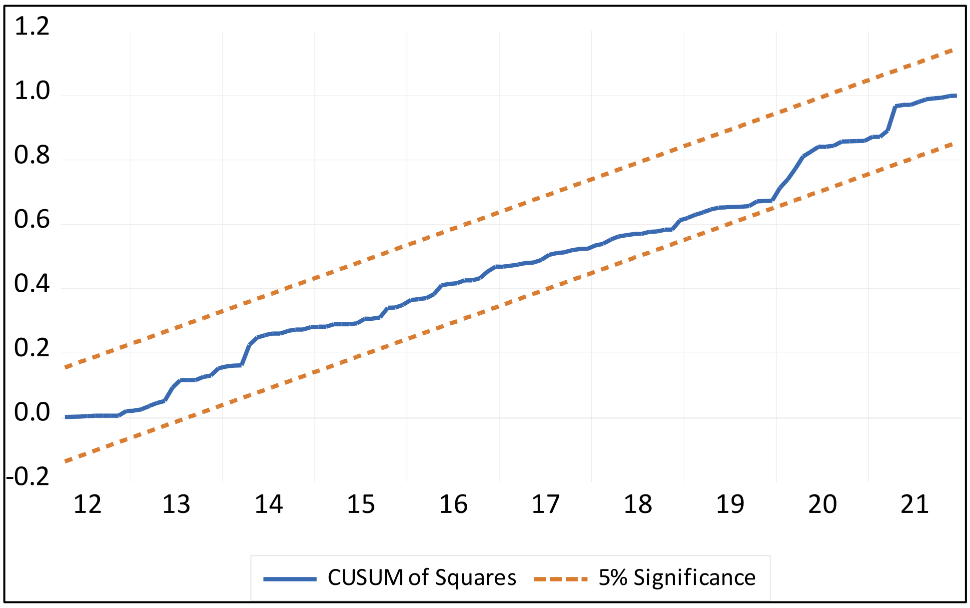

Figure 3: CUSUM of Square Test Results

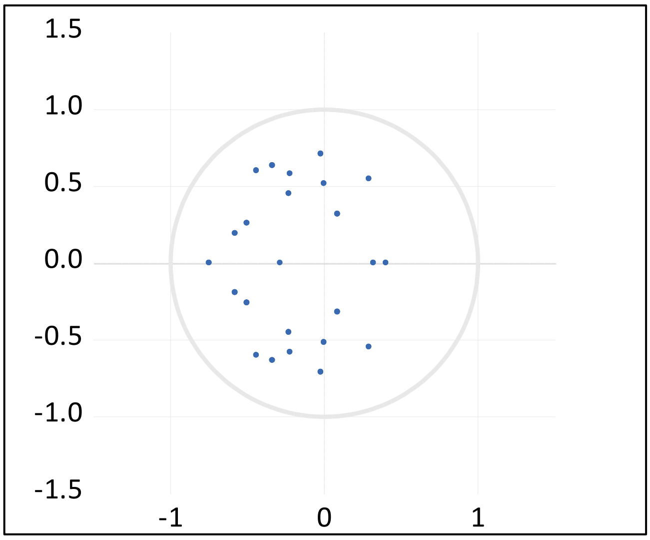

Figure 4: Inverse Roots of AR Characteristics Polynomial

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Appendix-A: Variables Used as a Proxy to the Investor Sentiment

Sr. No.	Variable	Description
1	MKTTURN	Market turnover (₹)
2	NUMTRADE	Number of trades
3	TRADEQTY	30 days moving average of traded quantity of shares
4	TVR	Trading volume ratio (the ratio of turnover ratio to standard deviation of the market returns for the particular month)
5	ADR	Ratio of number of the advancing shares to the number of declining shares
6	COMPTRAD	Proportion of the number of companies traded to the total number of companies listed
7	VIX	VIX™ (Volatility Index)
8	FPI	Foreign portfolio investment (₹)
9	PCR	Ratio of number of put options to the number of call options
10	PER	Price-earning ratio (Market price/Earning per share)
11	PBR	Price to book value ratio (Market price/Book price)
12	DIVYIELD	Dividend yield (Dividend distributed/Market price per share)
13	BSI	Buy-sell imbalance
14	FDI	Foreign direct investment (₹)
15	RTVOL	Retail trading volume (₹)
16	HLI	High-low index (10 days simple moving average of the record high percentage indicator)
17	EQRATIO	Ratio of equity (₹) in the total issue (₹)
18	NIFPO	Number of IPOs and FPOs in a month
19	ECORPREM	Difference between market return and the risk-free rate of return
20	XRETMP	Difference between return on market portfolio and market return
21	OILPRICE	Oil prices (₹)
22	BDEPMCAP	Ratio of bank deposit (₹) to market capitalization (₹)
23	EQMF	Net investment in equity by mutual fund companies (₹)
24	LIQECO	Liquidity in the economy as measured through M3 (₹)
25	INFLAT	Inflation in the economy as measured through whole sales price index
26	PLR	Level of interest rate as measured through prime lending rate
27	TERMSPRE	Term spread measured as the difference between 364 days treasury bills and 91 days treasury bills
28	IPI	Level of industrial production as measured through the industrial production index
29	SHORTINT	Short-term interest rate as measured through Short-term deposit interest rate
30	EXRATE	Exchange rate of the Indian rupee (₹) to US dollar ($)
31	FEXRES	Foreign exchange reserves of India (₹)
32	GDP	Gross domestic product

Appendix-B: Secondary Hypotheses

H_{0S1}: There is no significant relationship between “Market and Economic Variables (PC1)” and portfolio return.

H_{0S2}: There is no significant relationship between “Market Ratios (PC2)” and portfolio return.

H_{0S3}: There is no significant relationship between the “Advance-Decline Ratio and High-Low Index (PC3)” and portfolio return.

H_{0S4}: There is no significant relationship between the “Price to Book Value Ratio and Liquidity in Economy (PC4)” and portfolio return.

H_{0S5}: There is no significant relationship between “Oil Price and Industrial Production Index (PC5)” and portfolio return.

H_{0S6}: There is no significant relationship between the “Put-Call Ratio (PC6)” and portfolio return.

H_{0S7}: There is no significant relationship between “Ratio of Equity in Total Issues and Total Number of Issues (PC7)” and portfolio return.

H_{0S8}: There is no significant relationship between “Buy-Sell Imbalance and Foreign Direct Investment (PC8)” and portfolio return.

H_{0S9}: There is no significant relationship between “Trading-Volume Ratio (PC9)” and portfolio return.

H_{0S10}: There is no significant relationship between “Extra Return on Market Portfolio (PC10)” and portfolio return.

H_{0S11}: There is no significant relationship between “Term-Spread (PC11)” and portfolio return.

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Appendix-C: Estimation Command

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ARDL(DEPLAGS=3, REGLAGS=3) SENSEXRETURN PC1 PC2 PC3 PC4 PC5 PC6 PC7 PC8 PC9 PC10 PC11 @

Estimation Equation:

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

SENSEXRETURN = C(1)*SENSEXRETURN(-1) + C(2)*SENSEXRETURN(-2) + C(3)*SENSEXRETURN(-3) + C(4)*PC1 + C(5)*PC1(-1) + C(6)*PC1(-2) + C(7)*PC2 + C(8)*PC2(-1) + C(9)*PC3 + C(10)*PC4 + C(11)*PC5 + C(12)*PC5(-1) + C(13)*PC6 + C(14)*PC7 + C(15)*PC8 + C(16)*PC8(-1) + C(17)*PC8(-2) + C(18)*PC9 + C(19)*PC9(-1) + C(20)*PC10 + C(21)*PC10(-1) + C(22)*PC10(-2) + C(23)*PC11 + C(24)*PC11(-1) + C(25)

Substituted Coefficients:

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

SENSEXRETURN = 0.0557394887921*SENSEXRETURN(-1) - 0.102179486698*SENSEXRETURN(-2) + 0.290318091537*SENSEXRETURN(-3) - 0.0461560635617*PC1 - 0.0144113992174*PC1(-1) - 0.0168322193193*PC1(-2) - 0.00143128156979*PC2 - 0.00622044075748*PC2(-1) + 0.00863913417772*PC3 - 0.0174813086081*PC4 + 2.45006155395e-05*PC5 + 0.0035617635347*PC5(-1) - 0.00204478205405*PC6 - 0.0014783075728*PC7 - 0.00804730833579*PC8 - 0.00930850656024*PC8(-1) - 0.0093747956171*PC8(-2) + 0.000735354346139*PC9 - 0.00321612291388*PC9(-1) - 0.00276527538925*PC10 - 0.00412461429917*PC10(-1) - 0.00843244113214*PC10(-2) - 0.00223834861187*PC11 + 0.00311202550183*PC11(-1) + 0.00834414761523

Cointegrating Equation:

D(SENSEXRETURN) = -0.756121906369*(SENSEXRETURN(-1) - (-0.10236403*PC1(-1) -0.01011969*PC2(-1) + 0.01142558*PC3 -0.02311970*PC4 + 0.00474297*PC5(-1) -0.00270430*PC6 -0.00195512*PC7 - 0.03535225*PC8(-1) -0.00328091*PC9(-1) -0.02026437*PC10(-1) + 0.00115547*PC11(-1) + 0.01103545))

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