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Does Investor Sentiment Affect Volatility in the Indian Stock Market? An ARDL Approach

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Abstract

In a first of its kind, this paper discovers the long-run relationship between investor sentiment and Indian stock market volatility over the period 2010 to 2021, using monthly data. Twenty-two variables have been identified and used as proxy for investor sentiment. Then, using principal component analysis, the first 11 principal components with an eigen value of more than one have been selected and used as sentiment sub-indices, which represent the sentiments of Indian investors. The volatility of the S&P BSE 500 index has been measured using the GARCH model. We have applied the auto-regressive distributed lag (ARDL) model to document the relationship between sentiment and volatility. Further analysis has been done using ARDL modelling, by taking sentiment sub-indices as independent variables and the S&P BSE 500 Index GARCH volatility as the dependent variable. The value of was found to be 0.752. The results show that most of the sentiment sub-indices have a negative impact on the Indian stock market volatility in the long run. Thus, it can be concluded that in the long run, when sentiment is positive, volatility is negative, and vice versa. This study would be a valuable addition to the existing body of literature on the subject, besides being useful to regulators, policy makers, and investors. Regulators and policy makers should watch out for the impact of fluctuations in selected sentiment sub-indices on volatility in the stock market. Investors can search for arbitrage opportunities in the market on the basis of selected indices.

Keywords: Auto Regressive Distributed Model, Behavioural Finance, GARCH, Investor Sentiment, Principal Component Analysis, Risk, Sentiment, Sentiment Index, Volatility

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

Introduction

Behavioural finance is a response to rationality models of modern finance. It is a departure from rationality, and the decision-making patterns are explained with the help of models which incorporate the investors' irrationality (Barberies & Thaler, 2003). Rational investors, who are the cornerstone of modern finance, have been replaced by irrational investors. These irrational investors are termed as noised traders (Black, 1986). Irrational investors do not use the market fundamentals for decision making (Shleifer & Summers, 1990); rather, their decisions are influenced by their sentiments. The importance of sentiment in asset pricing was first enshrined by Keynes (1936) and other authors such as Black (1986) and De Long et al. (1990).

Sentiment is not directly observable; however, efforts have been made in this regard (Sehgal, Sood & Rajput, Investor Sentiment in India: A Survey, 2009). A survey is said to be a direct method using which sentiment can be observed; however, quantification is still not possible. Baker and Wurgler (2004) proposed that proxies can be used to represent the sentiments. The 'top-down' and

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'bottom-up' approach were developed by Baker and Wurgler (2006, 2007) for the measurement of sentiment and to examine its impact on asset price.

There is no consensus among authors on the number of proxies for sentiment. In a first of its kind, in this study we tried to use as many proxies as possible, after a thorough study of the literature. Initially, 22 proxies were used. After applying principal component analysis, we obtained 11 principal components using Kaiser (1960) criterion. These principal components have been called as the final sentiment proxies that represent the sentiment of Indian investors.

Efforts have been made to measure the sentiments and analyse their impact on stock returns. A few studies have analysed their impact on volatility. Volatility is usually defined as the standard deviation of equity returns. It is one of the important aspects of modern finance. A security is said to be efficiently priced if the expected returns on it is in proportion to the risk assumed by the investor.

Volatility plays an important role in the financial markets and affects one or many aspects of the market, such as changes in fundamental factors, nature of expectation of investors, investor's perception towards risk, differences in information, imbalances between demand and supply of securities, and so on. Fundamental factors comprise macro-level socio-economic-political factors, industry-specific factors like industrial policy of domestic and foreign governments, incentives and barriers in the movement of a product of a particular industry, seasonal factors, entry and exit policies, labour conditions, and so on, and company-specific factors like debt-equity mix, inventory valuation policies, policies regarding valuation of fixed assets, competence of management, financing, and investment and dividend decisions. In India, volatility has received attention, especially since early 1992.

It is an accepted fact that major fluctuations in security prices have significant negative effects on risk-averse investors. These also carry important economic implications, particularly for domestic investment and for the flow of funds from abroad for portfolio investment.

Volatility determines the extent to which people spend and save; it affects the prices of stocks, influences the prices of financial options, and thus, affects how investors might hedge investment risk. A person's decision about how much to spend today depends on how much income they expect their investment portfolio of stock to produce. If they expect a higher return from their investment portfolio, they may want to spend less and save more today. It is true otherwise as well. They may increase current spending in the hope that they may receive higher income in the future. Their decision depends on the degree of uncertainty about the return on stocks.

An increase in uncertainty affects the prices of stocks. If an investor is risk-averse, an increase in the uncertainty of returns on investment can lead them to sell the risky stocks and buy less risky securities like bonds/debentures. Since all other investors will also be doing the same, the current price of the stocks will fall due to the selling pressure. Thus, an increase in the uncertainty of returns can cause a decline in the current prices of the stocks.

The question arises whether there is any relationship between sentiment and market volatility. If yes, then how can this relationship be established? In this paper, we identify the sentiment proxies, measure volatility, and analyse the impact of sentiment on volatility.

The remainder of the paper is organised as follows. Section 2 presents the review of the literature. Section 3 gives the objectives and hypotheses of the study. Section 4 gives the research methodology and section 5 contains the results, along with the analysis. Section 6 concludes the paper.

Review of Literature

There is no place for sentiment in classical finance. However, in modern finance irrationality is an important aspect, so the popularity of sentiment is increasing. According to Fama (1965), irrational investors are not important in the asset pricing process. De Long et al. (1990) suggested that irrational investors are an important cornerstone of modern finance; they can drive the prices away from the market fundamentals on the basis of their irrationality. According to Baker and Wurgler (2006, 2007), the sudden ups and downs in the market are results of rapid investor sentiment.

Not all the shares are affected by the sentiment. According to Baker and Wurgler (2006, 2007), the shares of the following companies are affected by sentiment:

- New companies with low capitalisation;
- Companies paying no dividend;
- Companies with losses;
- Companies with volatility;
- Companies seeking growth; and
- Distressed companies.

Brown and Cliff (2004, 2005) concluded that there is a relationship between sentiment and cross-sectional expected returns. Kumar and Lee (2006) used retail trading as a proxy for sentiment and analysed its impact on stock returns.

Bandopadhyaya et al. (2008) reported that risk appetite measure, as developed by Persaud (1996) in the context of currency markets, can be used to measure investor sentiment in the equity market as well, using the data which is in the public domain. Using the methodology developed by Persaud (1996), Bandopadhyaya et al. constructed and measured EMSI[1] for the firms in an equity index (MBI[2]); it was concluded that EMSI and MBI are highly correlated and daily price movements in the MBI are significantly correlated with investor sentiment.

Chuang et al. (2010) showed that the trading volume can be used as a proxy for investor sentiment, and a negative and significant relationship between the volatility (conditional) and excess returns in the stock market of Taiwan was reported.

Sehgal et al. (2009) conducted a survey to identify the factors determining investor sentiment. Sehgal et al. (2010) constructed a sentiment index using the VAR model and analysed its relationship with market returns. The study concluded that it is difficult to establish a cause-and-effect relationship between sentiment and market returns.

Lux (2011) reported that results of weekly surveys on the forecasts of the stock market (over medium-run and short-run horizons) can be used to create diffusion indices for medium-run and short-run sentiment. Medium-run sentiment was found to be significant in predicting the returns.

Corredor et al. (2013) reported that there is a significant impact of sentiment on the returns, but it is not the same over various countries.

[1]Equity Market Sentiment Index.
[2]Massachusetts Bloomberg Index.

Bu and Bi (2014) reported that two kinds of sentiments, *viz.* optimism or pessimism of fundamentalists and sentiments of noise traders who are either bearish or bullish, are there in the market, and these sentiments affect the prices. It was shown that the sentiment index has a good projecting power about the CSI300 (China Securities Index 300) index.

Shing So and Lei (2015) examined the relationship between sentiment (noise signal) and trading volume. The study implied that if there is a relationship between sentiment and trading volume, then there must be a relationship between sentiment and market returns.

Kumari and Mahakud (2015) reported that investor sentiment in the Indian stock market can predict market returns and volatility. Kumari and Mahakud (2016) reported that the Indian aggregate sentiment index can predict volatility, and thus plays an important role in determining volatility. Naik and Padhi (2016) reported that conditional volatility can be explained by sentiment.

Jitmaneeroj (2017) reported that instead of getting into the trap of using PER as a proxy for sentiment as per the conventional analysis, it is better to explore whether PER affects sentiment. Using the latent variable analysis, the study showed that the changes in PER are not only due to fundamental factors, but also due to investor sentiment, which is one of the important factors responsible for the changes in PER.

Khan and Ahmed (2019) created a composite sentiment index using direct and indirect proxies for sentiment. The study concluded that there was a positive relationship between market returns and sentiment and market returns and lagged market returns, and a negative relationship between market returns and lagged sentiment.

Pandey and Sehgal (2019) constructed different sentiment indices. It was reported that the FF5f model fails to explain the excess returns of the small stock and low price to book value portfolio; however, after incorporating the investor sentiment factor, the model performed better. The study concluded that investor sentiment plays a very important role in the Indian stock market.

Gupta and Maurya (2021) analysed the trends in the Indian primary market and explored the factors which affect the level of activities in this market. It was reported that investor sentiment, along with the level of market valuation, affect the decision of the company to go public. Investor sentiment was measured through VIX™ (Volatility Index).

From the review of literature, it is evident that few studies have analysed the impact of sentiment on volatility. Further, the studies have used the approach developed by Baker and Wurgler (2004b, 2005, 2006) for the measurement of sentiment. In this paper, we have used a totally different approach to measure sentiment. Further, the long-run relationship of sentiment with market volatility has been analysed using the methodology proposed by Tripathi and Kumar (2015).

Objectives and Hypotheses of Study

Objectives of the Study

Following are the objectives of the study:

- To identify the proxies for investor sentiment.
- To analyse the relationship between investor sentiment and the Indian stock market volatility.

Hypotheses of the Study

To achieve the second objective, we have framed the following hypotheses:

H_{0P1}: There is no significant impact of sentiment sub-indices on stock market volatility.

H_{1P1}: There is a significant impact of sentiment sub-indices on stock market volatility.

Research Methodology

Data, Sources, and Time Frame

We have used data of approximately 12 years, *i.e.* from April 2010 to December 2021 (a total of 141 observations). While selecting this range we have not excluded the time period related to the pandemic, since during this period there were major drifts in the market, though for a short period.

Data has been collected from various sources, such as the websites of the RBI, SEBI, OECD, OFX, BSE, NSE, IMF, MCX, NSDL, CDSL, World Bank, the Association of Mutual Funds in India, Ministry of Statistics and Programme Implementation (Central Statistics Office), Department for Promotion of Industry and Internal Trade, Ministry of Commerce and Industry, Government of India, Central Statistics Organization, and Indexmundi.com.

Symbols used in the study have been provided in Appendix 2.

Identification of Proxies for Sentiment

Investor sentiment is not directly observable, though surveys can be used as a direct method to measure it. Academicians suggested that instead of direct methods, indirect methods can be used, under which some proxies can be used (Baker & Wurgler, 2004a, 2004b, 2006, 2007). To identify the proxies for investor sentiment, we have thoroughly studied the literature and arrived at the following 22 proxies.

Table 1: Proxies for 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 advancing shares to number of declining shares
6	COMPTRAD	Proportion of number of companies traded to total number of companies listed
7	FPI	Foreign portfolio investment (₹)
8	PCR	Ratio of number of put options to number of call options
9	PBR	Price to book value ratio
10	BSI	Buy-sell imbalance
11	FDI	Foreign direct investment (₹)
12	HLI	High-low index (10 days' simple moving average of the record high percentage indicator)
13	EQRATIO	Ratio of equity (₹) in the total issue (₹)

Sr. No.	Variable	Description
14	NIFPO	Number of IPOs and FPOs in a month
15	ECORPREM	Difference between market returns and risk-free rate of return
16	XRETMP	Difference between return on market portfolio and market returns
17	OILPRICE	Oil prices (₹)
18	BDEPMCAP	Ratio of bank deposit (₹) to market capitalisation (₹)
19	EQMF	Net investment in equity by mutual fund companies (₹)
20	LIQECO	Liquidity in the economy as measured through M3 (₹)
21	TERMSPRE	Term spread measured as the difference between 364 days' treasury bills and 91 days' treasury bills
22	IPI	Level of industrial production as measured through industrial production index

Data was tested for stationarity using the Augmented Dickey-Fuller test (Fuller, 1976) and the Phillips Perron test, at 1% level of significance (if -statistic is less than -critical value, then a series is stationary) (see Table 3). Eleven series were found to be non-stationary. To make the series stationary, we have taken first order difference. Next, data was standardised taking Z-scores for all the series. Principal component analysis was applied to the data and the first 11 principal components with eigen values more than 1 were taken (Kaiser, 1960). These 11 components explained 78.252% of the variation, and is acceptable for a model to be valid (Hair Jr., Anderson & Tatham, 1984).

The KMO test is a measure of how suitable the data is for factor analysis. A value less than 0.6 means that the sample is inadequate and needs remedial action. We get a value of 0.619, which is mediocre but more than 0.6. This means that the sample is adequate (Table 2). Bartlett's test of sphericity is run to see if there is redundancy among the variables, which can be summarised by a few numbers of components using the principal component analysis method. The null hypothesis of the test is that the variables are not correlated and the alternative hypothesis is that the variables are correlated. The value from this test is 0.000, which means that the data is suitable for running the data reduction technique, *i.e*. principal component analysis, on the data set.

The maximum factor loadings (Table 4) were the identified for each proxy and these proxies were grouped accordingly[3]. These 11 principal components are our sentiment sub-indices. These were suitably named to assign some meanings, and these sentiment sub-indices represent the sentiment of Indian investors (Table 5).

Table 2: KMO and Bartlett's Test

Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy		0.619
Bartlett's Test of Sphericity	**Approx. Chi-Square**	1043.813
	Df	253
	Sig.	0.000

Table 3: Test for Stationarity

Variables	*Augmented Dickey-Fuller Test*		*Phillips Perron Test*	
	Level	*First Difference*	*Level*	*First Difference*
	P Value	*P Value*	*P Value*	*P Value*
ADR	0	0	0	0.0001
BDEPMCAP	0.3362	0	0.4432	0
BSI	0	0	0	0.0001
COMPTRAD	0.1685	0	0.1739	0
ECORPREM	0	0	0	0.0001
EQMF	0	0	0.0001	0
EQRATIO	0	0	0	0.0001
FDI	0.7294	0	0	0.0001
FPI	0	0	0	0.0001
HLI	0.028	0.0001	0.0977	0
IPI	0.1145	0	0.0212	0.0001
LIQECO	0.9949	0	1	0
MKTTURN	0	0.4944	0.0125	0
NIFPO	0.2364	0.0005	0	0.0001
NUMTRADE	1	1	0.9664	0
OILPRICE	0.3015	0	0.3041	0
PBR	0.1902	0	0.1611	0
PCR	0	0	0	0.0001
TERMSPRE	0	0	0	0.0001
TRADEQTY	0.0265	0	0.0308	0
TVR	0.0161	0	0	0
XRETMP	0	0	0	0.0001

[3]Due to brevity of space, detailed results of principal component analysis are not provided here; however, they can be made available on demand.

Table 4: Factor Loadings

Variables	*Components*										
	1	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*11*
MKTTURN		.814									
NUMTRADE		−.786									
TRADEQTY		.791									
TVR									.866		
ADR			.858								
COMPTRAD	−.583										
FPI	−.732										
PCR						.798					
PBR				−.692							
BSI								.819			
FDI								.552			
HLI			.789								
EQRATIO							.772				
NIFPO							.802				
ECORPREM	−.842										
XRETMP										.888	
OILPRICE					.840						
BDEPMCAP	.600										
EQMF	.750										
LIQECO				.815							
TERMSPRE											.979
IPI					.636						

Note: Only maximum factor loadings have been shown.

Source: Author's own compilation.

Table 5: Sentiment Sub-Indices

Principal Component	*Name of the Principal Component, i.e. Final Sentiment Proxy*
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 economy
PC5	Oil price and industrial production index
PC6	Put-call ratio
PC7	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
PC11	Term-spread

Source: Author's own compilation.

Investor Sentiment and Volatility

To examine the impact of investor sentiment on volatility, we have set the null hypothesis (see 3.2. Hypotheses of the Study). To test the null hypothesis, sentiment sub-indices have been used as independent variables and market volatility is the dependent variable. GARCH volatility of S&P BSE 500 has been used as a proxy for market volatility. We have used EViews 12 to calculate the GARCH volatility series.

Pesaran et al. (1996) introduced the ARDL approach. We have used this model in EViews 12 to analyse the long-run relationship sentiment sub-indices and volatility in the Indian stock market. We have followed the methodology as proposed by Tripathi and Kumar (2015). EViews gives the ARDL model with optimal lag length. An auto-regressive distributed lag model is defined as follows:

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

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 ARDL model is one of them. A series is said to be stationary if its mean, variance, and auto-covariance are time invariant. We have used the Augmented Dickey-Fuller (ADF) method to test the stationarity of our sentiment sub-indices (Taghizadeh & Ahmadi, 2019). All the sentiment sub-indices were found to be stationary at level (at 1% level of significance), since the series of all of the original variables were stationary at first difference. Results of unit root test applied on sentiment sub-indices are reported in Table 6.

Table 6: Unit Root Test Results for Sentiment Sub-Indices

Sentiment Sub-Indices	*T-Statistic*	*Probability*
PC1	−13.30413	0.000
PC2	−11.33955	0.000
PC3	−17.22338	0.000
PC4	−16.94444	0.000
PC5	−10.27386	0.000
PC6	−10.65050	0.000
PC7	−9.636241	0.000
PC8	−11.46551	0.000
PC9	−13.56784	0.000
PC10	−12.65277	0.000
PC11	−8.991572	0.000

Source: Author's own calculation.

Results and Data Analysis

Measurement of GARCH Volatility

Fig. 1 gives the graph of the monthly return of S&P BSE 500 Index. In the graph we see that the line goes above and below the 0 line, which shows evidence of volatility.

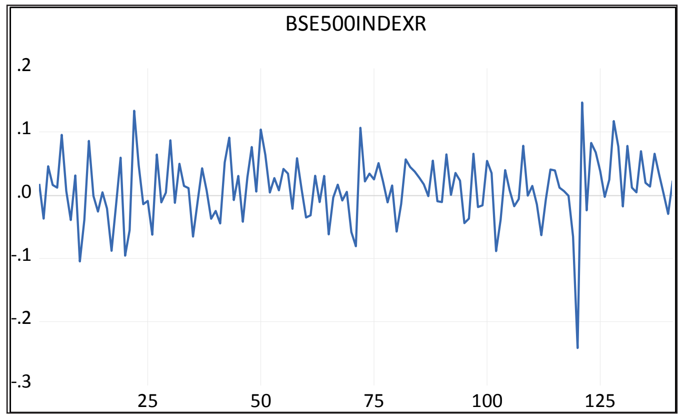


Fig. 1: Graph of S&P BSE 500 Index Return

The nature of the series of returns may be non-stationary. So, before we apply the GARCH model, we should check the series for unit root. For checking the stationarity, we have applied Augmented Dickey-Fuller test, the results of which are given in Table 7.

Table 7: Stationarity Test for S&P BSE 500 Index

Null Hypothesis: BSE500INDEXR has a unit root				
Exogenous: Constant				
Lag Length: 0 (Automatic – based on SIC, maxlag = 13)				
			T-Statistic	*Prob.**
Augmented Dickey-Fuller test statistic			−12.09344	0.0000
Test critical values:	1% level		−3.477487	
	5% level		−2.882127	
	10% level		−2.577827	
*MacKinnon (1996) one-sided p-values.				
Augmented Dickey-Fuller Test Equation				
Dependent Variable: D(BSE500INDEXR)				
Method: Least Squares				
Sample (adjusted): 2 141				
Included observations: 140 after adjustments				

Variable	*Coefficient*	*Std. Error*	*T-Statistic*	*Prob.*
BSE500INDEXR(−1)	−1.029173	0.085102	−12.09344	0.0000
C	0.010369	0.004438	2.336549	0.0209
R-squared	0.514514	Mean dependent var.		3.68E−05
Adjusted R-squared	0.510996	S.D. dependent var.		0.073687
S.E. of regression	0.051528	Akaike info criterion		−3.079191
Sum squared resid.	0.366412	Schwarz criterion		−3.037168
Log likelihood	217.5434	Hannan-Quinn criter.		−3.062114
F-statistic	146.2514	Durbin-Watson stat		1.998691
Prob(F-statistic)	0.000000			

Source: Author's own compilation.

The p value is 0.000, which suggests that the series is non-integrated. This means it is stationary at level.

We have checked the series of S&P BSE 500 index returns for the ARCH effect. It is necessary to do so because the pattern of volatility must follow the ARCH family models. We apply the ordinary least squares equation (Equation 1) in the EViews 12 to test whether the return of the current month is based on the previous month's returns. Results are given in Table 8.

$$BSE500INDEXR\ C\ BSE500INDEXR(-1) \ldots\ldots\ldots.(1)$$

Now we check the series for heteroscedasticity or the ARCH effect. Results are shown in Table 8.

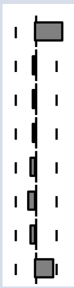
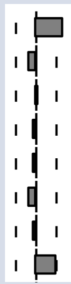
Table 8: Testing for ARCH Effect

Heteroscedasticity Test: ARCH				
F-statistic	6.703233	Prob. F(1,137)		0.0107
Obs*R-squared	6.483844	Prob. Chi-Square(1)		0.0109
Test Equation:				
Dependent Variable: RESID^2				
Method: Least Squares				
Sample (adjusted): 3 141				
Included observations: 139 after adjustments				
Variable	*Coefficient*	*Std. Error*	*T-Statistic*	*Prob.*
C	0.002051	0.000555	3.696448	0.0003
RESID^2(−1)	0.216103	0.083468	2.589060	0.0107
R-squared	0.046646	Mean dependent var.		0.002620
Adjusted R-squared	0.039688	S.D. dependent var.		0.006128
S.E. of regression	0.006005	Akaike info criterion		−7.378088
Sum squared resid.	0.004941	Schwarz criterion		−7.335865
Log likelihood	514.7771	Hannan-Quinn criter.		−7.360930
F-statistic	6.703233	Durbin-Watson stat.		1.971258
Prob(F-statistic)	0.010663			

Source: Author's own compilation.

The probability for the null hypothesis of the homoscedasticity is 0.000, which means we reject the null hypothesis and accept the alternate hypothesis that heteroscedasticity is present in the series. So, there is strong evidence that the ARCH effect is present in the series of returns. We also calculated the squared residuals to test the probability of the ARCH order. Results are in Table 9.

Table 9: Correlogram Squared Residuals

Date: 09/07/22 Time: 19:39					
Sample (adjusted): 2 141					
Included observations: 140 after adjustments					
Autocorrelation	Partial Correlation	AC	PAC	Q-Stat	Prob
		1 0.216	0.216	6.6633	0.010
		2 -0.014	-0.064	6.6927	0.035
		3 -0.019	-0.002	6.7442	0.081
		4 -0.020	-0.017	6.8016	0.147
		5 -0.030	-0.025	6.9317	0.225
		6 -0.059	-0.050	7.4477	0.281
		7 -0.031	-0.010	7.5960	0.370
		8 0.147	0.160	10.852	0.210

Source: Author's own compilation.

Squared residuals (Table 9) and top partial correlations give an idea of how many ARCH effects can be fitted. It can be seen that the first three terms are statistically significant, but after that the terms do not seem to be appropriate. So, adding three ARCH components is appropriate, since the value is less than 5% level of significance. However, the second and third partial correlations seem to be irrelevant on the basis of their values. So, we estimate the ARCH(1,1) test and include one residual.

The above analysis permits us to go ahead in estimating the GARCH(1,1) model. We have estimated the GARCH(1,1) model in EViews 12 with EViews Legacy optimisation method. Results are shown in Table 10.

Table 10: GARCH(1,1) Model

Dependent Variable: BSE500INDEXR				
Method: ML ARCH – Normal distribution (Marquardt / EViews legacy)				
Sample (adjusted): 2 141				
Included observations: 140 after adjustments				
Convergence achieved after 72 iterations				
Pre-sample variance: backcast (parameter = 0.7)				
GARCH = C(3)+C(4)*RESID(−1)^2+C(5)*GARCH(−1)				
Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.013173	0.004152	3.172470	0.0015
BSE500INDEXR(−1)	−0.107016	0.084970	−1.259465	0.0479
	Variance Equation			
C	0.002533	0.001031	2.456864	0.0140
RESID(−1)^2	0.301923	0.095792	3.151856	0.0016
GARCH(−1)	−0.248837	0.334930	−0.742951	0.4575
R-squared	−0.006767	Mean dependent var.		0.010077
Adjusted R-squared	−0.014062	S.D. dependent var.		0.051364
S.E. of regression	0.051724	Akaike info criterion		−3.104563
Sum-squared resid.	0.369206	Schwarz criterion		−2.999504
Log likelihood	222.3194	Hannan-Quinn criter.		−3.061870
Durbin-Watson stat.	1.860398			

Source: Author's own compilation.

We see that the past returns have a strong negative effect on the current returns, with a significance level of 5%. This shows that the current volatility goes into the switch of volatility. Now we make the GARCH variance series, which will be our dependent variable.

Sentiment Sub-Indices and Volatility

Equation 2 (lags are given in parentheses) gives the ARDL model, and the results are reported in Table 11. The equation with substituted coefficients and integrated coefficients are given in Appendix 1.

$$
\begin{aligned}
&GARCHVOLATILITY \\
&\quad = C(1).GARCHVOLATILITY(-1) + C(2).GARCHVOLATILITY(-2) \\
&\quad + C(3).PC1 + C(4).PC1(-1) + C(5).PC1(-2) + C(6).PC1(-3) \\
&\quad + C(7).PC2 + C(8).PC2(-1) + C(9).PC3 + C(10).PC3(-1) \\
&\quad + C(11).PC3(-2) + C(12).PC3(-3) + C(13).PC4 + C(14).PC4(-1) \\
&\quad + C(15).PC4(-2) + C(16).PC4(-3) + C(17).PC5 + C(18).PC5(-1) \\
&\quad + C(19).PC6 + C(20).PC7 + C(21).PC8 + C(22).PC8(-1) \\
&\quad + C(23).PC8(-2) + C(24).PC9 + C(25).PC9(-1) + C(26).PC9(-2) \\
&\quad + C(27).PC9(-3) + C(28).PC10 + C(29).PC11 + C(30) \ldots\ldots\ldots (2)
\end{aligned}
$$

Table 11: ARDL Model Equation and Results

Dependent Variable: GARCHVOLATILITY				
Method: ARDL				
Sample (adjusted): 2010M08 2021M12				
Included observations: 137 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: 12582912				
Selected Model: ARDL(2, 3, 1, 3, 3, 1, 0, 0, 2, 3, 0, 0)				
Variable	*Coefficient*	*Std. Error*	*t-Statistic*	*Prob.**
GARCHVOLATILITY (−1)	−0.052939	0.081042	−0.653231	0.5150
GARCHVOLATILITY (−2)	0.190191	0.075782	2.509716	0.0136
PC1	−0.000493	0.000130	−3.800798	0.0002
PC1(−1)	0.000799	0.000202	3.954503	0.0001
PC1(−2)	0.000563	0.000203	2.766031	0.0067
PC1(−3)	0.000251	0.000144	1.738716	0.0850
PC2	−3.60E−05	0.000115	−0.313205	0.7547
PC2(−1)	0.000201	0.000132	1.523833	0.1305
PC3	9.48E−05	0.000130	0.731133	0.4663
PC3(−1)	**0.000491**	**0.000131**	**3.758050**	**0.0003**
PC3(−2)	0.000262	0.000134	1.950601	0.0537

Variable	*Coefficient*	*Std. Error*	*t-Statistic*	*Prob.**
PC3(−3)	0.000240	0.000125	1.919520	0.0576
PC4	**0.000646**	**0.000167**	**3.878008**	**0.0002**
PC4(−1)	0.000334	0.000174	1.923943	0.0570
PC4(−2)	0.000437	0.000170	2.564602	0.0117
PC4(−3)	−0.000213	0.000163	−1.306006	0.1944
PC5	**−0.000281**	**0.000116**	**−2.418156**	**0.0173**
PC5(−1)	−0.000285	0.000125	−2.274857	0.0249
PC6	−0.000132	0.000108	−1.215220	0.2270
PC7	−4.81E−05	0.000105	−0.456255	0.6491
PC8	3.88E−05	0.000140	0.276865	0.7824
PC8(−1)	1.10E−05	0.000155	0.070830	0.9437
PC8(−2)	**−0.000420**	**0.000160**	**−2.627250**	**0.0099**
PC9	0.000220	0.000128	1.714329	0.0894
PC9(−1)	**−0.000310**	**0.000131**	**−2.359875**	**0.0201**
PC9(−2)	6.59E−05	0.000144	0.458173	0.6478
PC9(−3)	**0.000525**	**0.000132**	**3.962911**	**0.0001**
PC10	−3.08E−05	0.000108	−0.284033	0.7769
PC11	2.24E−05	9.37E−05	0.239332	0.8113
C	**0.002268**	**0.000302**	**7.500045**	**0.0000**
R-squared	0.751559	Mean dependent var.		0.002675
Adjusted R-squared	0.684224	S.D. dependent var.		0.001902
S.E. of regression.	0.001069	Akaike info criterion		−10.65420
Sum squared resid.	0.000122	Schwarz criterion		−10.01479
Log likelihood	759.8130	Hannan-Quinn criter.		−10.39436
F-statistic	11.16155	Durbin-Watson stat.		2.028933
Prob(F-statistic)	0.000000			

*5% Level of Significance.
Source: Author's own calculation.

The of this model is 0.752. F-statistic is significant at 5% level of significance, which means that coefficients are not equal. Results reveal that the Indian stock market volatility is significantly explained by itself, PC1, PC3, PC4, PC5, PC8, and PC9. Volatility can be explained by its own past values at second lag at 5% level of significance. Indian stock market volatility has a significant negative relationship with the current value of PC1 and PC5. Volatility is positively related with the lagged value of PC3 and the current value of PC4. It is negatively related with the current value of PC5 and the second lagged value of PC8; and positively related with PC9 at first and third lag. Results also show that the Indian stock market volatility is not explained by its own lagged values, PC2, PC6, PC7, PC10, and PC11.

Fig. 2 gives the graphical representation of the ARDL model. Here, we see that the fitted values of the Indian stock market volatility are close to the actual values.

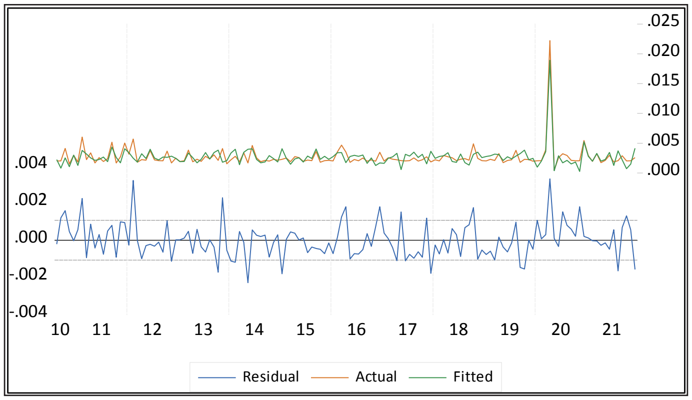


Fig. 2: ARDL Model Graph

We have analysed our model for the determination of the long-term relationship between the Indian stock market volatility and sentiment sub-indices using the ARDL bound test (Peseran et al., 2001). If the F-statistic is greater than the value of the upper bound, it shows that there is cointegration. If the F-statistic is between the value of the upper and lower bound, it shows that the result is inconclusive. If the F-statistic is less than the value of the lower bound, it shows that there is no co-integration. According to the results given in Table 12, the calculated values of F-statistic (Wald test) is equal to 8.385861, which shows the significant relationship between volatility and sentiment sub-indices with optimal delay.

Table 12: ARDL Model F-Bound Test Results

F-Bound Test		*Null Hypothesis: No Levels Relationship*		
Test Statistic	*Value*	*Signif.*	*I(0)*	*I(1)*
			Asymptotic: n = 1000	
F-statistic	8.385861	10%	1.76	2.77
K	11	5%	1.98	3.04
		2.5%	2.18	3.28
Actual Sample Size	137		Finite Sample: n = 80	
		10%	−1	−1
		5%	−1	−1
		1%	−1	−1

Source: Author's own calculation.

For the existence of convergence, it is necessary that the F-statistic be more than the upper bound . Based on the test, the existence of the independent convergence vector between the Indian stock market volatility and sentiment sub-indices was proven, indicating that there is a long-run relationship between volatility and sentiment sub-indices. Results are significant at all levels of significance (1%, 2.5%, 5%, and 10%).

Table 13: Restricted Constant and No Trend

Levels Equation				
Case 2: Restricted Constant and No Trend				
Variable	*Coefficient*	*Std. Error*	*t-Statistic*	*Prob.*
PC1	0.001298	0.000606	2.140594	0.0346*
PC2	0.000191	0.000214	0.890909	0.3750
PC3	0.001261	0.000359	3.511835	0.0007*
PC4	0.001395	0.000360	3.875024	0.0002*
PC5	−0.000656	0.000195	−3.356898	0.0011*
PC6	−0.000153	0.000128	−1.196454	0.2342
PC7	−5.57E−05	0.000123	−0.454264	0.6506
PC8	−0.000430	0.000446	−0.962936	0.3378
PC9	0.000580	0.000475	1.221651	0.2245
PC10	−3.57E−05	0.000126	−0.283276	0.7775
PC11	2.60E−05	0.000109	0.239297	0.8113
C	0.002629	0.000108	24.41538	0.0000*

$$EC = GARCHVOLATILITY - (0.0013.PC1 + 0.0002.PC2 + 0.0013.PC3 + 0.0014.PC4 - 0.0007.PC5 - 0.0002.PC6 - 0.0001.PC7 - 0.0004.PC8 + 0.0006.PC9 - 0.0000.PC10 + 0.0000.PC11 + 0.0026)$$

5% Level of Significance.
Source: Author's own calculation.

Further, long-run coefficients are listed in Table 13, which shows that sentiment sub-indices PC1, PC3, PC4, and PC5 have a significant long-run effect on volatility at 5% level of significance. As far as other sentiment sub-indices are concerned, they are all statistically insignificant.

Now we run the error correction form test to check whether our model adjusts monotonically. The value of is −0.862748 with a value of 0.0000. This shows that the model will adjust monotonically. Results are shown in Table 14.

Table 14: Error Correction Form

ECM Regression				
Case 2: Restricted Constant and No Trend				
Variable	*Coefficient*	*Std. Error*	*t-Statistic*	*Prob.*
D(GARCHVOLATILITY(−1))	−0.190191	0.058376	−3.258056	0.0015
D(PC1)	−0.000493	9.50E−05	−5.189260	0.0000
D(PC1(−1))	−0.000814	0.000166	−4.888735	0.0000
D(PC1(−2))	−0.000251	0.000112	−2.232983	0.0276
D(PC2)	−3.60E−05	7.34E−05	−0.490058	0.6251
D(PC3)	9.48E−05	0.000101	0.942434	0.3481
D(PC3(−1))	−0.000502	0.000134	−3.738545	0.0003
D(PC3(−2))	−0.000240	9.03E−05	−2.653519	0.0092
D(PC4)	0.000646	0.000117	5.497542	0.0000
D(PC4(−1))	−0.000224	0.000156	−1.433877	0.1545
D(PC4(−2))	0.000213	0.000124	1.718344	0.0886
D(PC5)	−0.000281	8.14E−05	−3.450323	0.0008
D(PC8)	3.88E−05	7.59E−05	0.510464	0.6108
D(PC8(−1))	0.000420	8.18E−05	5.138135	0.0000
D(PC9)	0.000220	8.89E−05	2.474073	0.0149
D(PC9(−1))	−0.000591	0.000105	−5.638678	0.0000
D(PC9(−2))	−0.000525	8.45E−05	−6.210760	0.0000
CointEq(−1)*	−0.862748	0.078353	−11.01101	0.0000

Source: Author's own calculation.

We also check our ARDL models for serial correlation through the Breusch-Godfrey Lagrange Multiplier (LM) test. Results given in Table 15 show that the null hypothesis of no serial correlation is accepted at 5% level of significance. Thus, our ARDL model is free from serial correlation.

Table 15: Breusch-Godfrey Serial Correlation Lagrange Multiplier (LM) Test

Null hypothesis: No serial correlation at up to 1 lag			
F-statistic	0.220085	Prob. F(2,106)	0.6399
Obs*R-squared	0.283859	Prob. Chi-Square(1)	0.5942

Source: Author's own calculation.

CUSUM stability test result of the model in Fig. 3 shows that the ARDL model lies well within the 5% significance limits shown by the red lines, and thus, the model is stable.

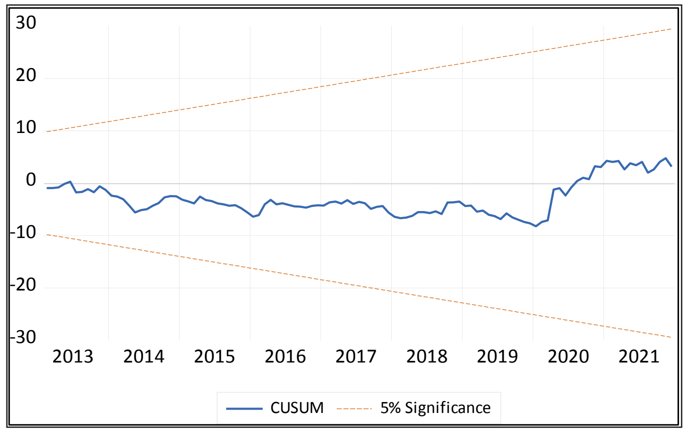


Fig. 3: CUSUM Stability Test Results

Conclusion

We have examined the interesting issue of whether sentiment sub-indices influence volatility in the Indian stock market. By applying Auto Regressive Distributed Lag (ARDL) model on sentiment sub-indices and stock market GARCH volatility monthly data for the period April 2010 to December 2021, we tested for long-run dynamic relationship. On the basis of extensive literature review and data availability, we identified 22 proxies for the sentiment. These 22 proxies were then 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 leading representative stock market stock index S&P BSE 500 has been used to calculate market volatility by applying the GARCH model. We have got some new insights. Market volatility is related to its own lagged values, though at second lag.

Market volatility has a significant negative relationship with its lagged values, and lagged values of oil price and industrial production index. Further, current values of market and economic variables have a positive significant relationship with volatility. It is interesting to note that we found no relationship of put-call ratio, ratio of equity in total issues and total number of issues, and trading volume ratio with volatility, which have been considered proxies for the investor sentiment by many studies. Similarly, market ratios, buy-sell imbalance and foreign direct investment, extra return on market portfolio, and term-spread are not related to volatility, as the stock market already discounts information on these.

Thus, based on the results, the hypothesis of this study, indicating the long-run relation between sentiment sub-indices and market volatility, cannot be refuted. After the determination of the order of VAR based on Akaike's information criterion, we have estimated the vector error correction model. The obtained ECM coefficient of −0.862748 shows that the speed of deviation adjustment from short-term to long-run is slow. One of the reasons for this may be that Indian investors wait for a long time period for the market to revive before they start investing again.

Results of the study are useful for regulators, policy makers, and the investors' community. Regulators and policy makers should watch out for the impact of fluctuations in different sentiment sub-indices. The investment community can search for the presence of exploitable arbitrage opportunities in the Indian stock markets to earn above-normal returns on the basis of sentiment sub-indices, but not on the basis of market ratios, put-call ratio, ratio of equity in total issues and total number of issues, buy-sell imbalance and foreign direct investment, trading-volume ratio, and term-spread indices.

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Appendix 1: ARDL Equation with Substituted Coefficients and Integrated Equation

Equation with Substituted Coefficients:

$$
\begin{aligned}
GARCHVOLATILITY &= -0.0529392317299.GARCHVOLATILITY(-1) \\
&+ 0.190191177021.GARCHVOLATILITY(-2) \\
&- 0.000492758817659.PC1 + 0.000798520540465.PC1(-1) \\
&+ 0.000562646562168.PC1(-2) \\
&+ 0.000251089567288.PC1(-3) - 3.59687952163e - 05.PC2 \\
&+ 0.000200818721699.PC2(-1) + 9.47685931739e - 05.PC3 \\
&+ 0.000491379830304.PC3(-1) + 0.00026182560097.PC3(-2) \\
&+ 0.00023974369858.PC3(-3) + 0.000645763991941.PC4 \\
&+ 0.000334369580037.PC4(-1) \\
&+ 0.000436718341424.PC4(-2) - 0.00021310826766.PC4(-3) \\
&- 0.000280894412425.PC5 - 0.000284971687928.PC5(-1) \\
&- 0.000131834218529.PC6 - 4.80926119037e - 05.PC7 \\
&+ 3.87694778379e - 05.PC8 + 1.09544306848e - 05.PC8(-1) \\
&- 0.000420299311776.PC8(-2) + 0.000219926988951.PC9 \\
&- 0.00030993022616.PC9(-1) + 6.58981158894e \\
&- 05.PC9(-2) + 0.000524810966851.PC9(-3) \\
&- 3.0802287055e - 05.PC10 + 2.24344066695e - 05.PC11 \\
&+ 0.00226846210066
\end{aligned}
$$

Cointegrating Equation:

$$
\begin{aligned}
D(GARCHVOLATILITY) \\
&= -0.862748054709(GARCHVOLATILITY(-1) \\
&- (0.00129760.PC1(-1) + 0.00019108.PC2(-1) \\
&+ 0.00126076.PC3(-1) + 0.00139524.PC4(-1) \\
&- 0.00065589.PC5(-1) - 0.00015281.PC6 - 0.00005574.PC7 \\
&- 0.00042953.PC8(-1) + 0.00058036.PC9(-1) \\
&- 0.00003570.PC10 + 0.00002600.PC11 + 0.00262934))
\end{aligned}
$$

Appendix 2: Symbols Used for Variables

BSEINDEXR: S&P BSE 500 Index Return

GARCHVOLATILITY: Volatility Measured using GARCH(1,1) Model