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The relationship of market sentiment and sector return across time and frequency – a wavelet coherence analysis

Versha Patel[1+]
S. Amilan[2]
P Vairasigamani[3]

[1,2,3]*Department of Commerce (Karaikal Campus), School of Management, Pondicherry University, India.*
[1]*Email: vershapatel93@gmail.com*
[2]*Email: amilancoursefaculty@gmail.com*
[3]*Email: sarojasamy1997@gmail.com*

(+ Corresponding author)

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ABSTRACT

Investment diversification is a strategic approach to mitigating risks by spreading assets across various sectors. Each sector has its unique temperament when it comes to market sentiment. Certain sectors are more prone to being influenced by sentiment, while others are less so. Conventional approaches often overlook the dynamic interaction between market sentiment and sector returns. The study utilized data from the Bombay Stock Exchange and National Stock Exchange, including all sectoral indices of the BSE from April 2008 to June 2023. A composite sentiment index was developed using Principal Component Analysis. The study employed Wavelet coherence to measure the association between market sentiment and stock returns of different sectors across time and frequency domains. The findings reveal that non-cyclical sectors like Tech, Health, IT, Telecom, Energy, and FMCG exhibit less sensitivity to fluctuations in sentiment and are less volatile, as these sectors provide indispensable services. Sectors such as Commodities, Financial Services, Industrial, Metal, and Auto show stronger coherence with sentiment, as they exhibit cyclical patterns and are connected with economic circumstances, making them more prone to market volatility. These insights help institutional investors and portfolio managers develop risk-adjusted strategies, align investments with risk tolerance, and balance short-term sentiment analysis with long-term fundamentals.

Contribution/Originality: This study was conducted across all BSE sectors. Unlike traditional methods, wavelet analysis utilizes time-frequency analysis and captures both short- and long-term dynamics, offering deeper insights. A sentiment index, constructed using technical indicators, the VIX, and other variables, explained the maximum variance, enhancing the robustness of the results.

1. INTRODUCTION

Classical finance theory assumes rational investors and a flawless market, largely ignoring the role of emotions. According to Fama (1965), the Efficient Market Hypothesis (EMH) suggests that stock prices quickly incorporate all available information, resulting in the law of one price and eliminating opportunities to outperform the market by exploiting price differences. This perspective emphasizes rational arbitrageurs who correct mispriced assets to their true value. Rational expectation theory assumes that investors make better decisions using publicly available information, past experiences, and psychology. However, in practice, traditional finance theories often fail to account for real-world complexities. Noise trader theory posits that incomplete and ambiguous information can cause anomalies, frequently driven by hype or rumors about future events, which push asset prices away from intrinsic value without reverting to the mean. These dynamics can significantly influence financial decision-making. Unlike these neo-classical models, behavioral finance offers an explanation for such anomalies and pricing discrepancies by analyzing human psychology and behavioral biases that lead to investor irrationality, affecting the financial market.

Investors' random expectations, speculative bubbles, Irrational exuberance, noise, uncertainty, and erroneous beliefs are all factors affecting investor sentiment. Building on this, Black (1986); De Long, Shleifer, Summers, and Waldmann (1990a) and De Long, Shleifer, Summers, and Waldmann (1990b) created a theoretical framework to explain market anomalies such as excess volatility, overreaction, and under-reaction by incorporating sentiment into asset pricing models. Sentiment has become crucial in asset pricing, especially due to noise traders who respond to non-fundamental news, greatly increasing systemic risk. The unobservable nature of sentiment makes it challenging to quantify. Academics have attempted to address these issues by devising three approaches to quantify sentiment: surveys, sentiment proxies, and direct measures. Given the dominance of institutional investors in emerging economies like India, sentiment surveys are not widely applicable. Instead, researchers use proxy methods to quantify sentiments. The most popular of these methods is an indirect approach, which builds the composite sentiment index using proxies (Baker & Wurgler, 2006, 2007). The majority of this research was undertaken in developed nations, making it difficult to apply to emerging economies due to unpredictability, advanced technology, and financial literacy.

In emerging markets like India and other Asian developing nations, institutional investors dominate the market and are typically viewed as informed arbitrageurs with access to significant information. However, institutional investors in India often trade on noise, making prices informationally inefficient. Kumari and Mahakud (2015) examined BSE and NSE indexes, showing that investor sentiment significantly affects the conditional volatility of the Indian stock market. (Aggarwal & Mohanty, 2018) showed a strong positive link between sentiment and returns on major and sectoral indices.

This study builds upon and extends the work of Aggarwal & Mohanty in three ways: Unlike the previous study, this research examines the relationship between market sentiment and stock market returns across all sectors of BSE, analyzing their interaction across various timeframes and frequency domains. This broader approach provides deeper and more robust insights compared to conventional methods that often overlook sector-specific variations. Second, the study constructs a sentiment index; it uses data on fundamental, technical, and macroeconomic variables from India alongside the US Economic Policy Uncertainty (EPU) index. This multidimensional approach ensures a more holistic measure of market sentiment, improving its predictive power. Thirdly, the study spans April 2008 to June 2023, covering almost 15 years and including major financial events. Conventional approaches assume a static relationship between market sentiment and sector returns despite the fact that they actually interact dynamically across different time periods and scales. Wavelet coherence can uncover dynamic associations, such as the impact of short-term sentiment on daily fluctuations and the influence of long-term patterns on market performance. This study seeks to address this gap by investigating the time-varying correlation between market sentiment and the performance of the Indian stock market.

The subsequent sections are structured as follows: The second section offers a review of the literature, examining studies that utilize indirect measures to establish proxies and their effects on stock returns and volatility. The third section discusses the data and methodology, detailing the selected variables and the development of the sentiment index. The fourth section presents the empirical findings and discusses the study. The concluding remarks are presented in the final section.

2. REVIEW OF LITERATURE

Research has demonstrated the importance of investor sentiment in financial markets, with numerous studies examining its effects on stock returns, volatility, and liquidity. Traditional finance theory initially disregarded subjective opinions, beliefs, and emotions, as its assumptions of rationality and efficient markets hindered the development of realistic theories (Blume & Friend, 1973). Shiller (2000) coined the term "irrational exuberance" to describe the irrational behavior of investors that can lead to unexpected economic booms and busts. In De Long et al. (1990a) proposed the DSSW theory of noise trader sentiment, which emphasized the constraints of arbitrage. Shleifer and Vishny (1997) expanded on this theory, demonstrating that noise traders respond to non-fundamental information, creating short-term arbitrage opportunities for those who exploit mispricing. These traders buy and sell securities, relying on rumors, emotions, or heuristics without research or professional advice. Their existence shows the theory's real-world relevance in financial markets. Historical events provide insights into irrational behaviors linked with crowd psychology that contribute to the formation of speculative bubbles (Mackay, 1841). Malcolm Baker and Wurgler (2006) identified that incomplete information about investor behavior can lead to sentiment-driven mispricing. Mispricing can increase price volatility and uncertainty and negatively impact financial markets. Together, these elements illustrate the influence of irrational behavior and sentiment-based factors on financial markets.

Many researchers studied the relationship between sentiment and the stock market (Campbell & Kyle, 1993; Daniel, Hirshleifer, & Subrahmanyam, 1998; De Long et al., 1990a, 1990b; Han & Kumar, 2013; Hong & Stein, 1999; Lakonishok, Shleifer, & Vishny, 1992; Qian, 2014; Shefrin & Statman, 1985; Shleifer & Summers, 1990). First, Brown and Cliff (2005) found that indirect investor sentiment measurements are linked to direct surveys and that emotion affects stock performance contemporaneously. Zweig's (1973) seminal work was one of the first to investigate sentiment indicators CEFD derived from market data that can predict returns. Lee, Shleifer, and Thaler (1991) discovered that closed-end funds are sentiment-driven and can be influenced by irrational trading by altering equity risk premiums, resulting in premiums or discounts compared to their underlying assets. Moreover, Ritter (1991) and Cornelli, Goldreich, and Ljungqvist (2006) found IPO data to be significant proxies for explaining the excess return; (Baker & Stein, 2004; Baker and Wurgler 2000) found equity issue to total issue and market liquidity as significant proxies for sentiment based on direct equity market activity. Secondly, Qiu and Welch (2004) showed that survey-based metrics like the consumer confidence index (CCI) can proxy sentiment. Instead of CEFD, the consumer confidence index best measures sentiment and is unrelated to stock prices. Others, including Verma and Verma (2007) and Verma and Soydemir (2009), employed AAII and II as sentiment proxies. AAII and II demonstrated a strong correlation between sentiment and mispricing (Brown & Cliff, 2004, 2005; Verma & Verma, 2007). Survey-based indicators are important for understanding sentiment and its impact on the financial market. Finally, Baker and Wurgler (2006) proposed a top-down proxy-based sentiment index. There was widespread respect for their work. They discovered that subjective, arbitrage-restricted stocks are heavily assessed by investors and affect cross-sectional returns. They used PCA of orthogonalized proxies and macro-variables to generate a composite sentiment index from six measures. Chen, Chong, and Duan (2010) used PCA of relative strength index, short-selling volume, money flow index, inter-bank rate, market turnover, and US and Japanese equity market returns to generate a sentiment index for emerging economies. Chen, Chen, and Lee (2013) measured sentiment in 11 Asian countries using a panel threshold model and turnover ratio. They found optimism (pessimism) overvalues (undervalues) industry returns. Yang and Zhou (2015) and Yang and Zhou (2016) show that the investor attitude effect using four sentiment proxies and the investor trading behavior effect on the excess return are both positive, supporting Yang and Gao (2014) in the stock index futures market. Ni, Wang, and Xue (2015) examined Shanghai A-share investor mood using turnover rate and opening accounts data. They found that equities with strong short-term (long-term) gains have favorable (negative) and large (small) sentiments from one month to two years. He, Zhu, and Gu (2017) developed a sentiment index employing ten sentiment proxies like consumer confidence and volume/value ratio and found a significant association between it and the Chinese Shanghai Stock Market index. Smales (2017) found that investor sentiment and stock returns are closely connected, with VIX being the most powerful sentiment indicator.

Despite extensive research conducted by Aggarwal and Mohanty (2018), Kumari and Mahakud (2015), and Prosad, Kapoor, and Sengupta (2015) on developing a market sentiment index and its correlation with stock returns, there is no established standard regarding the number of indicators to gauge public perception of the Indian stock market. Our study examines the strength of association across different time frames and the frequency domain to gain a deeper understanding of the causality and contagion behavior of investor sentiment and stock returns. This means that investors' emotions, attitudes, and opinions towards risk can play a crucial role in shaping the stock market's performance across time and frequency variations. Previous studies Aggarwal and Mohanty (2018); Malcolm Baker and Wurgler (2006); Malcolm Baker and Wurgler (2007); De Long et al. (1990a) and Kumari and Mahakud (2015) have shown a strong connection between investor sentiment and stock returns, suggesting that positive (negative) sentiment, or bullish (bearish), can lead to higher (lower) stock market returns. Thus, this study's hypothesis posits that changes in investor sentiment cause and spread contagiously with sectoral stock returns. Further research is needed to validate this hypothesis and to understand the extent of the coherence between investor sentiment and sectoral markets.

3. DATA COLLECTION AND METHODOLOGY

3.1. Data

This section examines the data and relevant variables used to build a sentiment index and determine its relation to the stock market. The time frame of this study spans from April 2008 to June 2023. The rationale for choosing the 15-year time frame is based on the availability of data for the selected proxies, including major financial events such as the Global Financial Crisis (GFC), COVID-19, and other market crashes. Since there is no uniform metric for gauging investor market sentiment, this study adopts an experimental approach by constructing an index using various proxy measures. These measures include indirect market indicators and macroeconomic variables for the Indian and United States markets. The data selection is based on availability, and each variable chosen in the study has theoretical relevance to the proxy measure employed in index development. Incorporating various fundamental, technical, and macroeconomic indicators will enhance the predictive ability of the index. Stock returns for BSE's Sensex, NSE's Nifty, and several sectoral indices of BSE are calculated using Equation 1. An overview of the aforementioned indices above, along with descriptive information, is provided in Table 1.

$$R_t = Ln\left(\frac{P_t}{P_t - 1}\right) \qquad (1)$$

Table 1. Indices and its descriptive and summary statistics.

Variables used	Description	Type	Source
SENSEX 30	Returns of SENSEX 30	Dependent variable	BSE website
NIFTY 50	Returns of NIFTY 50	Dependent variable	NSE website
Sectoral_indices	All sectoral indices returns of BSE	Dependent variable	BSE website
BETA	BETA of all sectors	Fundamentals	Built-in model
ADV_DEC	Advance decline ratio	Fundamentals	BSE website
Bank_Rate	Bank rate	Macro-economic variable of India	RBI website
CCI	Commodity channel index	Technical indicator	Built-in model
CPI	Consumer price index	Macro-economic variable of India	Federal reserve economic data
Dividend_Yield	Dividend yield	Fundamentals	BSE website
EPU__INDIA	Economic policy uncertainty of India	Macro-economic variable of India	Federal reserve economic data
EPU_US	Economic policy uncertainty of the US	Macro-economic variable of the US	Federal reserve economic data
Exchange rate	Exchange rate (₹-$)	Macro-economic variable of India	RBI website
Fed_Rate	Federal rate	Macro-economic variable of the US	Federal reserve economic data
FII	Foreign institutional investor net investment	Macro-economic variable of India	RBI website
IIP	Index for industrial product	Macro-economic variable of India	Federal reserve economic data
MACD	Moving average convergence divergence	Technical indicator	Built-in model
MFI_	Money flow indicator	Technical indicator	Built-in model
PB_ratio	Price to book ratio	Fundamentals	BSE website
PE_ratio	Price to earnings ratio	Fundamentals	BSE website
OBV	On balance volume	Technical indicator	Built-in model
RSI	Relative strength index	Technical indicator	Built-in model
VIX	Volatility index	Fear index	Investing.com

Note: Summary characteristics of indices as on 21st August 2023.
Descriptive statistics of index returns for the time period April 2008 to June 2023
PB, Price to book ratio; PE, Price to earnings ratio; FMCG, Fast moving consumer goods; IT, Information technology; PSU, Public sector Units. Market capitalization is in INR billions.

3.1.1. Proxies Used for the Construction of the Sentiment Index

Since the beginning of behavioral finance and investor sentiment, academicians have found it challenging to quantify investor sentiment due to its unobservable characteristics. Psychological biases and beliefs underpin theoretical and applied proxies of sentiment. This study builds a composite sentiment index for the Indian stock market using the top-down macroscopic method (Baker & Wurgler, 2006, 2007). To develop the index, we considered the market's indirect measures and macroeconomic indicators from the Indian and United States stock markets. We intended to collect a wide range of indicators that represent the sentiment of the Indian stock market.

3.1.1.1. Fundamentals

The indirect measure of the market consists of a few fundamentals, i.e., price-to-book (P/B), price-to-earnings (P/E), and dividend yield. The P/E ratio indicates how much investors trust and are willing to pay for a company's profits. Similarly, the P/B ratio represents the market value relative to the firm's book value. A high ratio indicates that the stock trades above the company's book value. We anticipate that the P/E and P/B ratios positively correlate with market sentiment. In contrast, dividend yield is expected to negatively correlate with sentiment, as it is believed that the company is distributing a substantial portion of its earnings to investors instead of reinvesting for growth.

3.1.1.2. Technical indicators

Technical indicators aid in analyzing stock price movements to identify whether a trend will continue or reverse and gauge market and economic sentiment. For this, the study selected the Advance Decline Ratio (ADV_DEC), Relative Strength Index (RSI), Commodity Channel Index[1] (CCI), Money Flow Indicator (MFI), On-Balance Volume[2] (OBV), and Moving Average Convergence Divergence (MACD). The ADV_DEC is a prominent indicator of market breadth that is utilized and expected to favor market sentiment. It analyzes the number of stocks with higher closing prices from the previous day versus those with reduced closing prices. The RSI is computed using Equation 2, which indicates bullish or bearish market sentiment. A value of 70 or above denotes an overbought market, and 30 or below indicates an oversold market. Thus, we look for a positive relation with market sentiment.

$$\text{Relative Strength Index}_t = 100 - \left[\frac{100}{1+\frac{\text{Average gain}}{\text{Average loss}}}\right] \tag{2}$$

Using the commodity channel index[1], one can better identify price movements and the strength of prevailing trends. When the CCI falls below -100, an asset is said to be oversold; it is overbought when it rises beyond +100. It typically identifies cyclical turns in commodities, stocks, and other markets. It is calculated by the difference between a change in security price and its average price change over a given period, as shown in Equation 3.

$$CCI = \frac{1}{0.015}\ \frac{p_t - SMA(p_t)}{MD(p_t)} \tag{3}$$

The Money Flow Indicator is a momentum indicator that measures buying and selling pressure based on price and volume[2]. MFI is a leading indicator that can be utilized to detect potential trend reversals and to measure the strength of a trend.

A momentum indicator called MACD helps forecast shifts in market sentiment. It is determined by taking the difference between the EMA (Exponential Moving Average) for 12 time periods and the EMA for 26 time periods, as shown in Equation 4.

$$MACD\ Value\ (t) = EMA12\ (t) - EMA26\ (t) \tag{4}$$

On-Balance Volume[2] (OBV) is a technical indicator that utilizes volume data to forecast changes in stock prices. It is based on the idea that volume precedes price, so if volume is increasing while the stock price is flat or decreasing, it is a bullish sign. Conversely, if volume is decreasing while the stock price is flat or increasing, it is a bearish sign. Lastly, VIX is an investor's fear gauge index derived from stock option prices; it measures the perceived short-term volatility of the stock market. It has a negative relationship with market sentiment, as a high VIX is frequently associated with bearish emotions, and a low VIX with bullish sentiment.

3.1.1.3. Macroeconomic Variables

The Consumer Price Index (CPI) and the Index of Industrial Production (IIP) are economic indicators measuring different aspects of a country's economy. The CPI tracks household spending on a basket of goods and services, while the IIP measures the change in the production of a basket of goods and services across various industries. The level of FII investment in a country can be an indicator of the sentiment of foreign investors towards that country's economy and markets. We anticipate a favorable relationship between CPI, IIP, and net FII investment and market sentiment, as these indicators point to rising confidence and economic expansion.

The relation between the exchange rate (₹-$) and sentiment is complex, but a strong (weak) and appreciating (depreciating) currency is often associated with bullish (bearish) sentiment, which usually indicates investor confidence in the country's economy and willingness to invest in it. As a monetary policy tool, the bank rate affects the economy and financial markets. A low bank rate facilitates borrowing and spending, thereby boosting economic growth and asset prices. The relationship between EPU and sentiment is rarely unambiguous. However, a high level of policy uncertainty, as indicated by a high EPU index, is generally related to bearish sentiment since it signals investors are hesitant and less eager to invest in the market. Bhagat, Ghosh, and Rangan (2016) found evidence of a negative relationship between EPU India and Sensex in their study. US economic developments can resonate around the globe, including India. US interest rates and trade policies can affect capital and goods flows between India and the US, impacting the Indian economy. Therefore, along with the Fed rate, EPU-US is evaluated to determine its effect on market sentiment. Also, the movement of the US dollar directly impacts the Indian markets, as India's economy is closely tied to the US dollar as a major trading partner. A stronger dollar can make Indian exports less competitive, affecting economic growth and negatively impacting market sentiment in India. There can be a link between the Federal Reserve's interest rate policy and sentiment in the Indian stock market. Changes in the Federal Funds Rate can affect global market conditions and influence the flows of capital worldwide, including to and from emerging markets like India. A greater degree of unpredictability in US markets has a detrimental impact on trade ties. It propagates a pessimistic market mood, while higher Fed rates make investing in the Indian market less appealing, resulting in a money outflow from the Indian market back to the US market. The description of the variables is given in Table 2.

Table 2. Variables used and their description.

Sentiment proxies	PC1	PC2	PC3	PC4	PC5
ADV_DEC	0.151**	0.074	(0.132) ***	0.723*	0.125***
BANK_RATE	(0.385) *	0.748*	0.413*	(0.052)	0.013
CCI	0.663*	0.579*	(0.280) *	0.094	0.017
CPI	0.856*	(0.257) *	0.393*	0.137***	0.011
DIVIDEND_YIELD	(0.749) *	0.183**	0.534*	0.094	(0.022)
EPU__INDIA	(0.699) *	(0.132) ***	0.034	(0.071)	0.116
EPU_US	(0.109)	(0.745) *	(0.064)	0.297*	0.130***
EXCHANGE_RATE	0.771*	(0.250) *	0.519*	0.187**	(0.015)
FED_RATE	0.435*	(0.124) ***	0.344*	(0.354) *	0.495*
FII	0.074	0.421*	(0.234) *	0.448*	0.634*
MACD	0.850*	(0.110)	(0.016)	(0.311) *	(0.079)
MFI	0.506*	0.167**	(0.166) **	0.337*	(0.472) *
OBV	0.896*	(0.353) *	0.166**	0.025	0.047
PB_RATIO	0.128***	(0.052)	(0.747) *	(0.491) *	0.236*
PE_RATIO	0.833*	(0.240) *	(0.285) *	0.071	0.064
RSI	0.624*	0.497*	(0.372) *	(0.074)	(0.233) *
VIX	(0.579) *	(0.542) *	(0.160) **	(0.009)	(0.199) **
IIP	0.628*	0.320*	0.530*	(0.260) *	0.003
Variance	0.378	0.150	0.127	0.086	0.060
Cumulative Variations	0.378	0.528	0.656	0.742	0.802

Notes: ***, **, and * signifies statistical significance at the 10 percent, 5 percent, and 1 percent level, respectively.

3.2. Methodology

3.2.1. Construction of Index

The study utilized Principal Component Analysis (PCA) to construct the index using proxies for sentiment. The sentiment index will be built with the principal components (PCs) that explain the maximum variance and have the highest correlation with the expected sign. Equation 5 for the sentiment index is below.

$$Sentiment\ index = ADV\_DEC - BANK\_RATE + CCI + CPI - DIVIDEND\_YIELD - EPU_{INDIA} + EPU_{US} + EXCHANGE\_RATE + FED\_RATE + FII_{NET} + MACD + OBV + PB_{RATIO} + PE_{RATIO} + RSI - VIX + IIP + MFI \quad (5)$$

3.2.2. The Wavelet Coherence

Unlike traditional methods that examine the static relationship, wavelet coherence is employed to capture dynamic interactions across various time frames and frequency domains. This approach provides deeper insights into how sentiment influences various market segments over time, addressing sector-specific variations that conventional methods overlook. Therefore, after the index has been constructed, the study intends to examine the coherence between the two series, i.e., investor sentiment and stock returns of various sectors across time- and frequency-varying domains. For which wavelet coherence is required to be conducted using the below Equation 6.

$$R^2_{xy}\ (\tau, s)\frac{|S(s^{-1}\, W_{xy}\,(\tau,s))|^2}{S(s^{-1}|W_x(\tau,s)|^2).S(s^{-1}|W_y(\tau,s)|^2)} \quad (6)$$

The time series data x_t and y_t represent investor sentiment and stock returns for each sector. The smoothing operator S indicates time and scale, with the coherence measure $R^2(\tau, s)$ ranging between 0 and 1. A higher R^2 value indicates a stronger co-movement between the two series, while a lower value indicates weaker coherence. The contour graph illustrates the co-movement across time and frequency.

The color intensity indicates the strength of the co-movement. Cooler colors like blue represent weaker coherence, while warmer colors like red indicate stronger relationships. The horizontal axis displays the time frame, and the vertical axis shows the varying frequency, with the top axis representing higher frequency, fast-moving patterns, and the bottom axis representing lower frequency, slow-moving patterns, allowing observation at different scales. The cone of influence highlights an area where edge effects might distort the data. Data outside the cone of influence and at the edges may be unreliable and should be interpreted cautiously. Arrows in the graph provide additional insights: the right arrow indicates that the two series are moving together, while the left arrow shows they are moving in opposite directions. Upward and downward arrows depict the lead-lag relationship: the upward arrow indicates that the second time series is leading the first, and vice versa. For data processing, the null hypothesis suggests using AR (1) or AR (0); if not applicable, Monte Carlo simulations can be used for non-stationary and complex data (Torrence & Compo, 1998).

4. RESULTS AND DISCUSSION

4.1. Construction of Sentiment Index

The study utilized all 18 proxies of investors' sentiment over the 182 monthly observations. These proxies were used to construct a composite sentiment index using a methodology proposed by Baker and Wurgler to evaluate the common variation and separate the common components. We expected that the components included in our analysis would account for at least 80% of the total variation, so the first 5 principal components (PCs) were considered for further analysis. Subsequently, we analyzed the correlation between sentiment proxies and the first 5 PCs. The results show that PC1 has the highest correlation with sentiment proxies at a significant level, with expected signs (negative/positive), and explains the maximum variance of 38%, as shown in Table 3. Therefore, we have chosen the loading of PC1 to develop the sentiment index as shown in Equation 7.

Table 3. Correlation of all sentiment proxies with the first five principal components.

Sentiment proxies	PC1	PC2	PC3	PC4	PC5
ADV_DEC	0.151**	0.074	(0.132) ***	0.723*	0.125***
BANK_RATE	(0.385) *	0.748*	0.413*	(0.052)	0.013
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EXCHANGE_RATE	0.771*	(0.250) *	0.519*	0.187**	(0.015)
FED_RATE	0.435*	(0.124) ***	0.344*	(0.354) *	0.495*
FII	0.074	0.421*	(0.234) *	0.448*	0.634*
MACD	0.850*	(0.110)	(0.016)	(0.311) *	(0.079)
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IIP	0.628*	0.320*	0.530*	(0.260) *	0.003
Variance	0.378	0.150	0.127	0.086	0.060
Cumulative variations	0.378	0.528	0.656	0.742	0.802

Notes: ***, **, and * signifies statistical significance at the 10 percent, 5 percent, and 1 percent level respectively.

$$Sentiment\ index = 0.058ADV\_DEC - 0.148BANK\_RATE + 0.254CCI + 0.328CPI - 0.287DIVIDEND\_YIELD - 0.268EPU_{INDIA} + 0.042EPU_{US} + 0.296EXCHANGE\_RATE + 0.167FED\_RATE + 0.028FII_{NET} + 0.326MACD + 0.344OBV + 0.049PB_{RATIO} + 0.319PE_{RATIO} + 0.239RSI - 0.222VIX + 0.241IIP + 0.194MFI \quad (7)$$

After constructing the sentiment index, we employed the Wavelet coherence measures, which analyze the strength of association between two-time series. It gives a local correlation over time as well as across frequencies. It is calculated by taking the ratio of the cross-spectrum to the product of the spectrum of two signals or time series.

4.2. Descriptive Statistics

This section discusses empirical results. Table 1 reveals the summary statistics for index returns and sentiment index. Descriptive statistics of Sensex indicate a 0.008% average monthly return. The minimum return is (0.273) %, and the maximum return is 0.248%, with a standard deviation of 0.060. The average monthly return of the Sensex over the period of the study is 0.008%. A kurtosis of 8.16 indicates that the tails are thicker, and a skewness of (0.77) indicates that the distribution curve is positively skewed to the left side. Figure 1 shows how the Sensex and Nifty returns have moved together, coupled with a composite sentiment index.

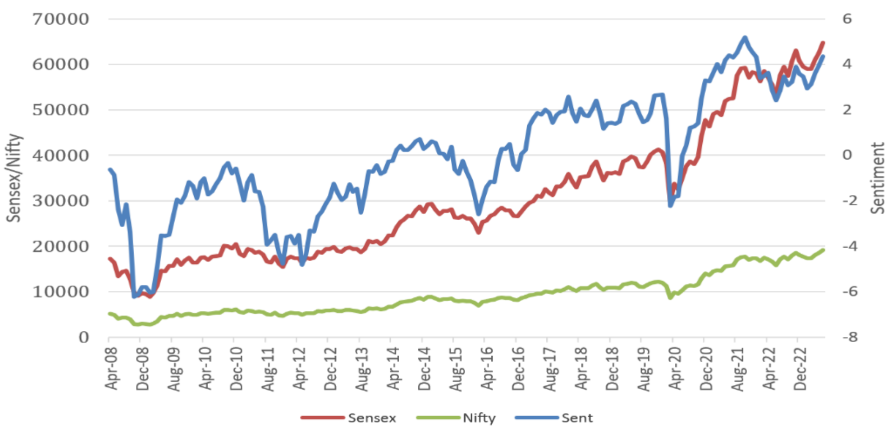

Figure 1. Co-movement of Sensex and Nifty along with composite sentiment index.

Table 4. Descriptive statistics of sentiment proxies.

Sentiment proxies	Mean	Median	Maximum	Minimum	Std.dev.	Skewness	Kurtosis
ADV_DEC	1.049	1.040	1.920	0.570	0.189	0.717	5.085
BANK_RATE	0.066	0.063	0.103	0.043	0.015	0.340	2.348
CCI	60.347	80.767	237.934	-232.669	95.343	-0.933	3.415
CPI	100.377	102.518	150.280	52.789	27.116	-0.005	1.951
DIVIDEND_YIELD	1.284	1.240	1.920	0.720	0.234	0.366	3.138
EPU__INDIA	100.362	88.944	283.689	23.353	48.742	1.292	4.885
EPU_US	141.671	136.597	350.460	71.262	44.234	1.400	6.257
EXCHANGE RATE	62.324	64.374	82.610	40.022	11.417	-0.178	1.916
FED_RATE	0.008	0.002	0.051	0.001	0.011	2.039	7.022
FII_NET__BN_	63.661	64.450	710.460	-1182.030	221.633	-0.912	8.262
IIP	98.221	99.421	104.118	84.598	4.786	-1.147	3.590
MACD	1582.251	1291.427	5525.887	-1096.090	1401.218	0.929	3.641
MFI_CORRECT	53.159	53.426	78.779	17.550	11.088	-0.136	3.020
OBV	2628833.0	2363450.0	4341433.0	1492497.0	806624.5	0.658	2.269
PB_RATIOS	3.153	3.060	5.220	2.360	0.422	1.204	6.220
PE_RATIOS	21.639	21.190	35.130	11.880	4.480	0.700	3.589
RSI	60.757	60.590	90.894	18.339	15.286	-0.234	2.758
VIX	20.596	17.820	68.350	10.800	9.080	2.386	10.545

Note: Descriptive statistics of sentiment proxies chosen for study for the period April 2008 to June 2023.

PB, Price-to-Book ratio; PE, Price-to-Earnings ratio; ADV_DEC, Advance-Decline Ratio; CCI, Commodity Channel Index; CPI, Consumer Price Index; EPU, Economic Policy Uncertainty; FII, Net Foreign Institutional Investor Investment; IIP, Index for Industrial Production; ACD, Moving Average Convergence Divergence; MFI, Money Flow Index; OBV, On-Balance Volume; RSI, Relative Strength Index; VIX, Volatility Index Descriptive statistics of sentiment proxies from Table 4 reveal the fact that the majority of kurtosis values are greater than 3, implying that the data series is leptokurtic, except for exchange rate, CPI, Bank rate, and RSI. The series of exchange rate, RSI, MFI, and CPI are negative and highly skewed to the left, exhibiting a flatter and longer tail on the left side of the distribution. The Fed rate and VIX series are positive and highly skewed. The level of dataset variability is reflected by the standard deviation, with the bank rate and Fed rate exhibiting less variation and fewer fluctuations.

We conducted an Augmented Dickey-Fuller test to check for the presence of a unit root. The ADF test with trend and intercept revealed that the sentiment index is stationary at a 5% significance level with a p-value of 0.017 and t-statistics of 3.828, and the rest of the series is stationary at a 1% significance level. Since all series have an order of integration of 0, i.e., I(0), the study employed wavelet coherence analysis to examine the causal and contagion nature of investor sentiment and stock returns.

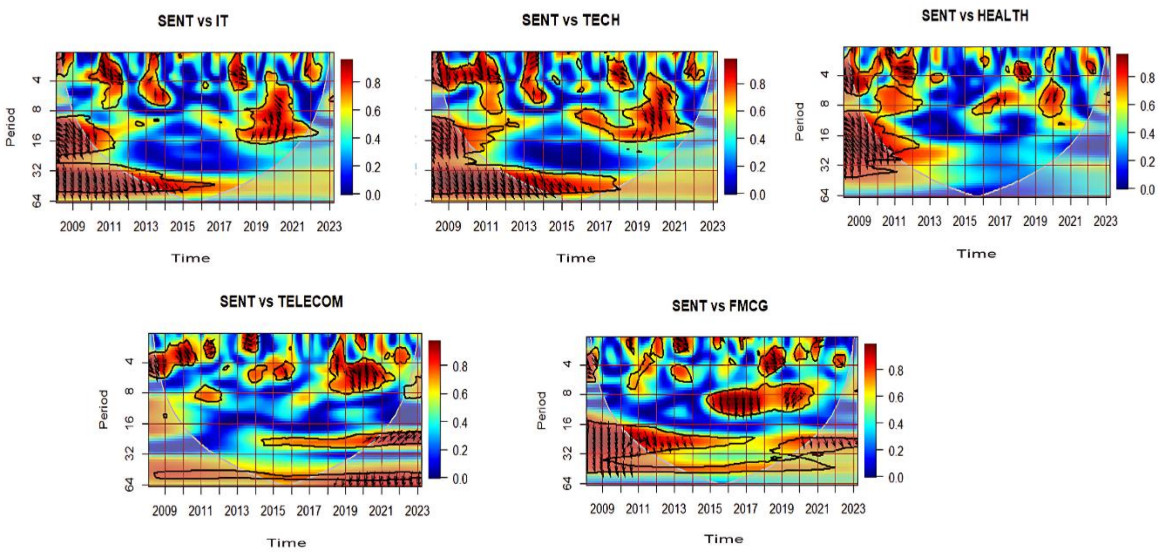

Figure 2. Co-movement of sentiment and sectors with weak coherence.

4.3. The Wavelet Coherence

The Tech, Health, IT, Telecom, Energy, and FMCG sectors exhibit relatively lower sensitivity to fluctuations in sentiment, as indicated by the cooler colors in their contour plots, as shown in Figure 2. A detailed examination of individual plots reveals the more specific relationship between investor sentiment and these sectors.

For instance, investor sentiment and the IT sector appear to have strong coherence from 2009 to 2015 at higher frequencies, and this strong coherence continues at a frequency in the 8 to 16 range during 2018-2022. The predominance of a downward arrow shows that investor sentiment is leading the IT sector during these comovement periods. The nexus of investor sentiment with the tech sector seems at higher frequency to have stronger coherence from 2008 to 2011, again in 2014, and then in 2019, and at 8 to 16 frequency from 2016-2022, with sentiment continuing to lead the tech sector indicated by a downward arrow. In contrast, the health sector across all frequencies, even during the pandemic, does not show any coherence with sentiment. The telecom sector seems to have slight coherence with sentiment at higher frequencies but does not appear to be coherent at lower frequencies. Lastly, the relationship between investor sentiment and FMCG demonstrates strong coherence at the 8-16 frequency range from 2015-2021, but it is not as coherent at higher frequencies.

These findings align with the nature of these sectors. It is often observed that the Tech, Health, IT, and FMCG sectors have a relatively lower degree of sensitivity to fluctuations in sentiment because they are considered non-cyclical sectors. These industries frequently demonstrate more predictable and enduring demand patterns. The technology and telecom (Tech) and healthcare industries are known for offering indispensable services and goods that are relatively less susceptible to immediate fluctuations with changes in sentiment. Information Technology (IT) organizations frequently exhibit recurring income streams and long-term contractual agreements, thereby reducing their reliance on sudden changes in sentiment and enhancing their overall performance stability. Fast-moving consumer goods (FMCG) companies provide essential products for daily use, and their offerings typically exhibit a relatively low price elasticity of demand. Therefore, fluctuations in consumer sentiment have a restricted influence on the sales of these companies. As a result, these industries are commonly perceived to exhibit greater resilience in the face of market volatility influenced by emotion. Nonetheless, it is important to acknowledge that all sectors can experience the impact of wider economic patterns and external influences, though with differing magnitudes. Overall, these sectors are less sensitive to sentiment and tend to be more resilient during economic downturns as they provide essential goods and services that people continue to buy even during recessions.

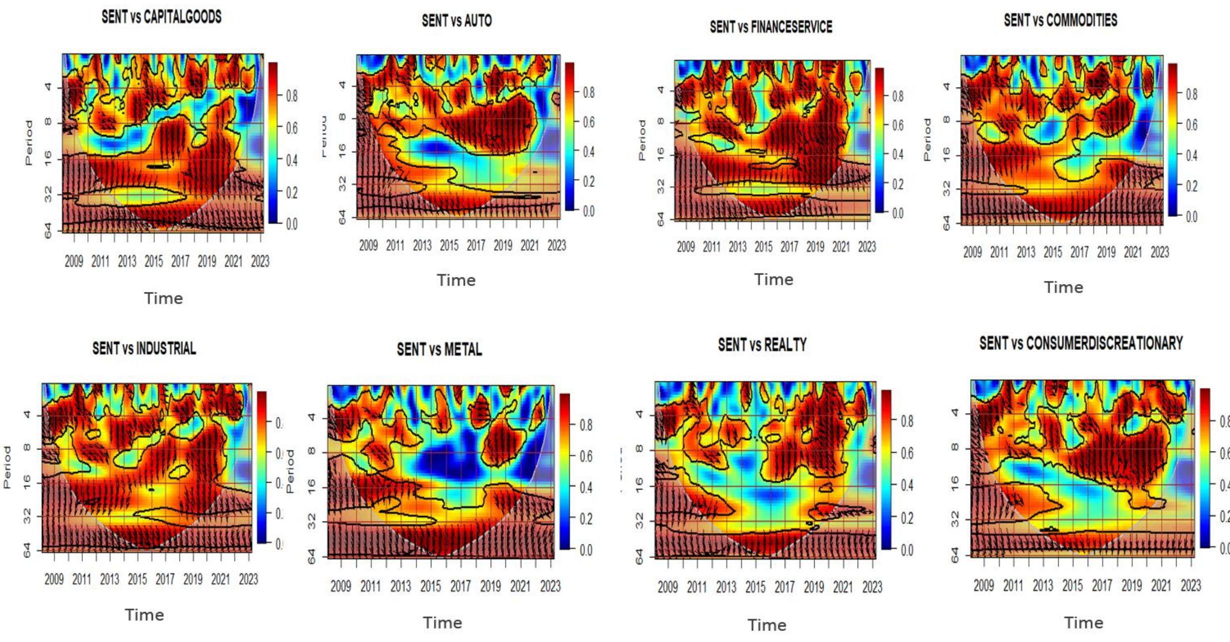

Figure 3. Comovement of sentiment and sectors with strong coherence.

In contrast, the Auto, Metal, Industrial, Financial Services, Consumer Discretionary, Real Estate, and Commodities sectors have stronger comovement with investor sentiment, as shown in Figure 3. Predominantly, the downward arrow indicates that investor sentiment is leading the different sectors, which implies sentiment has a strong influence on these sectors. Notably, sectors like industrial and financial services are relatively more coherent with investor sentiment across all time and frequency ranges.

The nexus of investor sentiment and the auto industry shows strong coherence at higher frequencies from 2009 to 2013 and again in the 4-16 frequency range from 2015 to 2021. The capital goods sector exhibits strong coherence with sentiment at both high and low frequencies, especially during COVID-19. Coherence between investor sentiment and commodities is evident at higher as well as lower frequencies, particularly prominent from 2008 to 2010. However, the comovement of the metal sector with investor sentiment appears to be warmer in color but shows relatively less coherence than other sectors. The nexus between investor sentiment and the real estate sector has stronger coherence in the 0-16 frequency range from 2017 to 2021. Lastly, the relationship between consumer discretionary and investor sentiment shows strong coherence in the 8-16 frequency range from 2015 to 2021. These are considered cyclical sectors and are therefore more volatile, as they offer dispensable services. Since their underlying fundamentals are distinct and they are vulnerable to different risks, these sectors are frequently intertwined due to their sensitivity to economic conditions, interest rates, and global trade dynamics.

The coherence of sentiment with various industries can be explained by their inherent characteristics, business models, and market dynamics. Sectors like Realty, Industrial, Metal, Financial Services, and Commodities exhibit a higher degree of sensitivity to changes in sentiment due to various factors. These industries frequently exhibit cyclical patterns and are closely connected with economic circumstances. Changes in sentiment can serve as an indicator of adjustment according to the economic condition, hence significantly impacting these industries. Financial Service enterprises have a high degree of sensitivity towards fluctuations in interest rates, which can significantly correlate with their profitability due to changes in investor sentiment. The real estate sector is influenced by consumer confidence and investment, making it more vulnerable to variations in demand driven by sentiment. The Metal and Commodities sectors are subject to the impact of several global economic factors, as well as the dynamics of demand and supply. It is important to note that sentiment fluctuations can exert a great impact on all of these aforementioned aspects. Therefore, all the above sectors are more sensitive to sentiment. Sectors frequently exhibit cyclical patterns and are closely connected with economic circumstances; they are more prone to market volatility.

This research examined different sector indices in India to find out how sentiment and sector stock returns move together. Our result confirms Baker and Wurgler's (2006) findings, which show that stocks that are appealing to optimists and speculators, stocks that are small, younger stocks, non-dividend-paying, distressed, unprofitable, and highly volatile stocks, tend to earn relatively low subsequent returns during periods of high sentiment. Similarly, the sectors that are cyclical in nature were found to be more driven by sentiment than the sectors with non-cyclical characteristics. Our research confirms the findings of Prosad et al. (2015) and Aggarwal and Mohanty (2018) that sentiment has a considerable effect on stock return.

5. CONCLUSION

This research investigates the empirical connection between investor sentiment and stock returns by creating a composite sentiment index and analyzing its coherence across time and frequency domains from 2008 to 2023. It was discovered that emotions easily sway investors' decision-making. Almost all sectors show a downward arrow, indicating sentiment is the leading factor for the industry. Similarly, the results of the analysis reveal that a change in investor sentiment significantly affects the returns of many sectors, which are cyclical and have heavy industrial and trading characteristics. Sectors indispensable in nature, such as health, tech, and FMCG, are important and non-cyclical in nature and not connected to the economic cycle. These factors all contribute to the distinct and unique risks faced by each sector, making it important to closely monitor and analyze their performance in order to make informed investment decisions. Hence, these sectors are closely tied to economic conditions and can greatly influence overall economic performance. This study's conclusion validates Aggarwal and Mohanty's (2018) assertion that sentiment affects stock returns, although their analysis did not examine the majority of sectors. The outcome demonstrated that FMCG, healthcare, and IT are more stable and unaffected by public opinion because they are less susceptible to economic fluctuations. However, stability may differ between sub-industries. Additionally, pandemics, technology, and consumer behavior may impact these areas. Keep abreast of market trends to make smart investments.

The findings suggest that investors interested in emerging markets like India will better understand the comovement between sentiment and sectoral indices' returns. The study will assist investors and policymakers. Retail and institutional investors should incorporate sentiments into asset pricing models as a systematic risk factor to enhance asset returns. Understanding how investor sentiment influences different sectors based on their volatility can help develop trading strategies and diversify portfolios. The study reveals that the market fear index, fundamentals, technical analysis, and macro factors influence investor sentiment. Policymakers can reduce market volatility by establishing stable policies, clear regulations, consistent monetary policy, and tax certainty. Stability and predictability encourage investment, which boosts liquidity and reduces volatility.

Further research can be conducted to better understand the relationship between investor sentiment and stock returns in the Indian market. This can be achieved by exploring different proxies for creating a sentiment index, as the construction of such an index has limitations, including the lack of consensus on the number of proxies to use. Additionally, analyzing its co-movement with other markets like energy and bullion can provide further insights. Using short-term temporal data, such as daily data, offers a deeper understanding of sentiment, as sentiment can change rapidly with significant events.

Notes:

1) For the purpose of producing the Commodity Channel Index, the index is typically scaled by an inverse factor of 0.015 to produce more readable data.

2) Volume is considered based on the monthly turnover of BSE from www.bseindia.com when calculating the On-balance volume and money flow index.

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