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Research paper

Investor Behavior Under Uncertainty: Sentiment and Herding Across Market Phases

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Abstract

Behavioral finance argues that investing behavior is influenced by emotions, biases, and cognitive ability (Almansour & Arabyat, 2017). The impact of behavioral shifts in investing has gained prominence in recent years. The COVID-19 pandemic sent waves of uncertainty to all spheres of life, even to the economic one. This study intends to examine the presence of herding behavior and investor sentiments in the Indian Stock Market, focusing on the benchmark index of Nifty 50. The impact was analyzed by focusing on three different phases, namely the pre-COVID phase, the crisis, and the post, COVID i.e. the recovery phase. Quantitative techniques were employed to measure the presence of investor sentiment and to detect herding patterns in the stock market. The results reveal significant behavioral shifts across the three phases, offering insights into sentimental investment decisions under crisis conditions. These findings hold relevance for market participants, policymakers, and researchers interested in behavioral finance.

Keywords: *E32; G11; G12; G14.*

1. Introduction

Stock market operations cannot be adequately explained by rational theories (Tversky and Kahneman, 1992). Investors are prone to non-rational decision-making behavior, particularly during times of distress. Behavioral finance accounts for these deviations in terms of psychological metrics like investor sentiment and herding. These metrics get activated particularly during periods of unprecedented volatility in the markets, e.g., when the COVID-19 pandemic crisis hit the economy, i.e., when fear, uncertainty, and speculation ruled the roost in the markets.

Financial markets are, by their nature, extremely sensitive to news, uncertainty, and collective emotions. Under unprecedented circumstances such as a pandemic, traditional models that depend only on economic fundamentals cannot properly explain the real determinants of prices. Instead, psychological and behavioral factors such as fear, speculation, and imitation become the prevailing forces driving market trends. It is at such moments that it becomes important to research not only what investors are doing, but why they are doing it, and how their activities collectively contribute to creating macroscopic market phenomena.

To comprehend patterns of herding and the role of sentiment in determining market outcomes is critical for both educational purposes but also for market efficiency improvement, investor education, and decision-making. It is a prime example of how emotional reactions can aggravate volatility and generate systemic dangers, especially during severe episodes such as the pandemic.

The pandemic of COVID-19 presented an all-time challenge to the economies and financial markets of the world. In India, the pandemic brought rapid changes in investor sentiment and market forces. This study focuses on the analysis of behavior patterns such as sentiment and herding in the Indian equities market during three different phases, namely the pre-COVID era, the pandemic phase, and the post-COVID i.e. recovery phase. Based on a focus on the Nifty 50 index, this research tries to grasp the manner in which collective investor sentiment influenced market behavior during this historic occasion.

Additionally, the Indian stock market offers a very interesting setting for these studies. Being an emerging market economy, it has both retail and institutional investors, which makes it prone to sentiment-based movement. The relatively high percentage of individual investors before the pandemic and the rapid emergence of online trading platforms added further to the magnification of the influence of emotions and mass psychology. This renders the Indian case an interesting one to study in the context of analysing the broader implications of investor psychology during periods of crisis.

2. Theoretical background

This section deals with the theoretical framework of the topics under consideration, validates the research methodology, and illustrates the existing background with crucial developments and findings in the subject area. The section summarizes the existing literature on the behavior patterns of herding and sentiments around the world in various stock markets and studies that deal with the impact of sentiment on herding.

2.1. Presence of herding behavior and investor sentiment in the stock market around the world

The impact of Geopolitical Risks on Herding Behavior in some Middle East and North Africa markets was analyzed by Imed Medhioub (2025). The study suggests that herding is more prominent during extreme downturns in all markets except Lebanon. The findings indicated that geopolitical tensions amplified the herding in Jordan and Tunisia, while the same witnessed a reduction of herding behavior in Lebanon. The presence of herding behavior on the Indian stock market was analyzed by Prakash et al. (2024), taking into consideration COVID-19. The model did not find any significant presence of herding from 2011 to 2019; however, behavior was evident during the crisis period (March to December 2020), likely due to emotional biases, fear, and uncertainty among investors. An analysis made by Pandey and Singh (2024) studied the herding behavior during the COVID-19 pandemic by using the Cross-sectional Absolute deviation (CSAD) method as the herding indicator. Their study found strong evidence of herding during bearish trends mainly due to the heightened uncertainty. Peng Yifeng (2024) explored the impact of investor sentiment in the Chinese A-share market. From this analysis, it is found that there is a positive impact on intraday overtrading. Moreover, sentiment-driven overtrading was mainly prevalent during the bull markets as compared to bear markets. Agarwal and Arora (2023) examined a dynamic panel data analysis to explore the relationship between investor sentiment and stock market volatility. By this study, it is clear that investor sentiment plays a crucial role in determining market volatility. Bhattacharyya and Lahiri's (2023) study focused on the impact of investor sentiment on stock market volatility in India. They concluded that investor sentiment significantly affects stock market volatility in periods of high sentiment, leading to increased volatility. The presence of investor sentiment was analyzed by Dunham and Garcia (2020), caused by Twitter content and news articles, on stock market liquidity. Their model found that improvements in investor sentiment from Twitter forced a decrease in the average firm's share liquidity, while deterioration in the same led to an increase in liquidity. Interestingly, the opposite pattern was identified for sentiment derived from news articles, where positive news sentiment increased liquidity and negative news sentiment reduced it. These findings magnified the differing impacts of social media and traditional news sentiment on market behavior. Smales (2017) investigated the impact of sentiment on stock return volatility, administering news-based sentiment indicators in the U.S. market. The findings showed that negative sentiment significantly strengthened market volatility, especially during economically sensitive timeframes. The model also suggested that sentiment, in lieu of economic fundamentals, described short-term market movements over the period of high-uncertainty periods. The results from the study pointed out the importance of sentiment in driving the irrational behavior of investors and weakening the strength to destabilize markets even in developed economies. A similar presence was found during the global financial crisis analyzed by Antoniou et al. (2013). They discovered that herding was particularly notable during the 2008 financial crisis, where investors, triggered by fear and panic, followed the acts of others, leading to the market collapse. This model amplified the importance of following the guidelines to stop the negative outcomes of herding during the periods of volatile market conditions, pointing out the chances of worsening the financial instability. Baker et al.(2012) studied the significance of indices measuring sentiment and their impact on stock returns. They modelled a study to track investor sentiment according to a range of financial variables, involving stock market returns, trading volumes, and the yield curve. Their analysis supported the perspective that positive sentiment boosted stock returns, but this effect was typically short-lived, as markets were likely to rectify when sentiment returned to further rational levels. Heston and Sadka (2008) discovered the link between sentiment and stock returns, pointing to the role of market sentiment indices like the VIX. This model analyzed that high volatility, as indicated by rising levels of the VIX, functioned as a strong indicator of negative sentiment, triggering lower stock returns. They also found that sentiment played an important role in elucidating returns during periods of high ambiguity, such as recessions or financial crises, pointing to the significant impact of sentiment on market behavior in the midst of volatile timeframes. Baker and Wurgler (2007) brought forward the concept of investor sentiment, linking it to stock market returns and volatility. They implemented that investor sentiment, influenced by both rational and irrational factors, can significantly affect stock prices, generally in the short term. Their sentiment index which is shown as one of the most widely used measures of market mood because it became a crucial tool in financial research for identifying the consequences of investor sentiment on market behavior. Kumar and Lee (2006) mainly concentrated on the ramifications of investor sentiment on stock returns. They pointed out that sentiment-driven herding can possibly lead to excessive stock returns in the short term, but frequently ends in corrections as market fundamentals reinforce themselves. Their study affirmed the cyclical nature of sentiment-driven outcomes in the stock market, with market trends driven by investor mood ultimately modifying when fundamentals took precedence. Sias (2004) analyzed the trading behavior of institutional investors and their consequences in herding behavior. He suggested that even if institutional investors are properly informed about the worst situations of the market, they tend to follow the crowd to avoid market crashes. Sias' study concluded that institutional herding can cause market destabilization because large volumes of trades will result in price distortions and market fluctuations. Brown and Cliff (2014) studied the impact of Investor sentiment on stock returns. They found that the positive sentiment can boost the stock prices, and this excessive optimism will lead to bubble formation in the short term. When the situation is reversed, there will be significant changes in the price level because of the volatility in the market. Hwang and Salmon (2004) studied the relationship between herding behavior and market volatility. They argued that herding behavior has played an important role in intensifying price movements, mainly during the periods of high market uncertainty. They have collected data from both emerging and developed countries, and the result disclosed that herding was more present in both emerging and developed countries, but market volatility was more present in emerging countries. The main reason behind this phenomenon was that investor behavior in these economies was less affected by fundamental analysis, making them close to the consequences of herding. Malkiel (2003) analyzed how herding behavior challenged efficient market hypothesis, which explains how all available information is present in the asset prices. By this study, he explains how herding behavior can cause uncertainty in the market, leading to bubbles and crashes. Malkiel's study also studied how this herding behavior linked the market inefficiencies and the rise of speculative bubbles and he provided valuable information about how this herding behavior contorted the asset prices and weakened the market efficiency. Lee et al. (2002) concentrates on the impact of investor sentiment on market volatility. And the results show that high level of sentiment can intensify the price movements in a market. If positive sentiment is present in the market, then there is greater market stability and on the contrary negative sentiment was evident, it can intensify ambiguity by causing increased market volatility and fluctuations in the stock prices. Gervais et al. (2001) explored the psychological factors of herding behavior by linking it to the biases such as overconfidence in the crowd and the situation where people are pressurised to follow socially. From this analysis, they have found that people are more forced to follow the crowd or contribute to herding when they are not sure about their own information or they felt pressure. And the research also shows the notable role of behavioral biases in magnifying herding tendencies, mainly when the investors face uncertainty or incomplete information. Bikhchandani and Sharma (2000) analyses the impact of herding behavior on financial markets in emerging economies. In the financial markets of emerging economies the information asymmetry was more prominent and investor behavior was mainly controlled by social influences. By this study they highlighted that herding in these markets can lead to greater volatility and mispricing of securities, as investors believe in the fundamental information and take decisions based on the actions of others. Wermers (1999) studied the impact of mutual funds and institutional investors on market behavior. The model shows that during the periods of high market volatility fund managers usually engaged in herding. Wermer's study concluded that institutional herding can cause mispricing of securities, as comprehensive buying and selling decisions are mainly determined by broad market movements more than the intrinsic value of assets. This herding behavior can cause ineffective market pricing and it might increase overall market volatility.

2.2. Impact of investor sentiment on herding behavior

The adaptive nature of herding behavior in global energy markets was investigated by Ooi Kok Loang (2025), focusing on the USA, Europe, and Asia. From the analysis, it is found that higher levels of investor happiness and positive market sentiment are connected with increasing herding behavior in the U.S.A. On the contrary, negative sentiments are connected with reduced herding behavior. Yang, Lin, and Cheng (2025) studied the impact of real-time public sentiment on herding behavior in Taiwan's stock market. This analysis mainly focused on different investor types and industries and the result shows that sentiment significantly affects herding behavior with influence being most pronounced in the electronics industry. Dong (2024) examined how behavioral biases—specifically overconfidence, herding, and loss aversion—shape investor sentiment and drive stock price volatility, particularly during events like the dot-com bubble and the 2008 financial crisis. The study emphasized the role of strong corporate governance mechanisms such as independent boards, executive compensation design, and risk management frameworks—in reducing the negative impact of investor sentiment. Ultimately, it argues that long-term corporate goals, transparency, and robust governance are essential for managing market sentiment and protecting shareholder value. Nait Bouzid Khalil et al. (2023) studied the impact of investor sentiment and herding behavior in the Chinese stock market. The author analyzed the monthly data and used the cybersecurity readiness index (C.I.C.S.I) as the proxy for sentiment. They concluded that there was no significant herding in the 2003-2018 period. However, when sentiment was high, generally within A-share markets dominated by retail investors, evidence of persistent herding emerged. Their study concluded that based on the market phase and stock type sentiment levels significantly influences herd intensity. Choi and Yoon (2020) analyzed the link between herding behavior and investor sentiment. By using regression analysis, they showed that investor sentiment had a positive and significant impact on herding behavior in the KOSDAQ stock market, while in the KOSPI stock market, the impact was not statistically crucial. From this analysis, it is evident that the impact of sentiment on herding behavior depends on the market characteristics.. studied herding behavior in the context of geopolitical risks and investor sentiment in the U.S Stock market. Their model found that investor sentiment deteriorates when geopolitical tensions intensify and it leads to stronger herding tendencies among market participants. These findings of Bouri and Roubaud has played an important role mainly during the periods of uncertainty, if investors are blindly following the crowd, then it shows the fear induced trading, resulting in deviations from the fundamentals. Litimi (2017) explored the causal relationship between investor sentiment and herding behavior, applying the Granger causality test. The model found that causality generally flows one way from the volatility index (VCAC) to the cross-sectional absolute deviation (CSAD), in all but three sectors— healthcare, consumer services, and technology—where a bidirectional relationship exists. Chau, Deesomsak & Koutmos (2016) analyzed sentiment-induced trading on the US stock market and found evidence that during stages of elevated investor sentiment, institutional investors frequently displayed trend-following herding behavior, whereas some traders acted reasonably by trading against the herd when prices were overheated. This pointed out that noise traders aren't always irrational, yet the combined effect of both irrational institutions and noise traders during high sentiment phases might still destabilize markets. Furthermore, Liao et al. (2015) studied herding and investor sentiment in the Spanish stock market. This study shows that investor emotion was a major driver of collective behavior. By using the Granger causality tests, they indicated that the past returns and sentiment significantly predicted the future herding. Their findings confirmed that sentiment can act as both a trigger and amplifier for herd behavior, generally during abnormal market phases. The authors pointed out the need to incorporate emotional and psychological variables in herding models to efficiently forecast and regulate market stability. Berisha and Pavlovska (2015) analyzed the relationship between investor sentiment and herding behavior in the Baltic stock market. And they found that a significant relation exists only in the Riga and Tallinn markets. They concluded that herding exists only when investors experience anxiety by indicating emotional factors like fear and ambiguity, as it increases herding tendencies in specific regional markets. Yao, Ma & He (2014) found herding in the Chinese market during the 2015 stock market turbulence. During the market boom and crash, the market is affected by crucial herding, and retail investors are influenced by sentiment and media narratives. The study concluded that sentiment magnified the herd dynamics, generally in sectors with high retail participation, and how sentiment-fueled herding can destabilize markets and end in mispricing. Chen, Jegadeesh, and Wermers (2000) studied whether mutual fund managers set herding as a source of aid in response to investor sentiment. By analysing through the composite sentiment index and the trinomial model of fund level herding, the study shows that the fund managers are more engaged in significant herding behavior mainly during the market is facing an overly optimistic sentiment challenge. While analysing both cases, herding was more prominent during sell decisions. The study shows the importance of informational cascades and the behavioral patterns that are sentiment-linked, pointing that institutional decisions are not influenced by market mood swings. Chiang & Zheng (2010) tested herding across 18 countries and opined that CSAD detects regional herding effects and contagion more robustly than MMI (Market Mood Index). Guedj & Bouchaud (2004) further investigated earnings forecasts by financial analysts across the US, UK, EU, and Japan between 1987 and 2004, focusing on herding and sentiment. They found that analysts were overoptimistic and exhibited herding behavior, as their forecasts aligned with each other 5 to 10 times more than with real earnings. During the late 1990s, this behavior was named the tech bubble, showing that positive sentiment can foster collective bias. This study questions the efficient market assumptions and shows how sentiment-driven herding can distort market expectations. A comprehensive review of herding behavior within capital markets was carried out by Hirshleifer & Teoh (2003), pointing to the role of investor sentiment, informational cascades, and reputational influences. Drawing from theory and empirical evidence across analysts, fund managers, and retail investors, they identified that herding often emerges when sentiment is intensified by reputation concerns or perceived knowledge of others, i.e., informational cascades. Their study highlighted that both positive and negative sentiment spikes can tend to market-wide cascading behavior—regardless of actual fundamentals. The authors identified that such sentiment-driven herding is pervasive across markets, and its detection is fundamental to behavioral finance and regulatory design. Chen et al. (2001) further studied how herding behavior and investor sentiment can influence market movements in an economy. And from the study, they analyzed that during the periods of overly optimistic sentiment, herding behavior plays a significant role in magnifying asset prices and market bubbles. On the contrary, if there is negative sentiment, herding behavior leads to a market downturn, increasing the effects of pessimism and leading to sharper declines in asset prices.

3. Hypothesis development

Based on the existing literature, the study seeks to identify the presence of herding behavior among investors and examine the role of investor sentiment in influencing stock returns in the Indian stock market. Additionally, it aims to assess the impact of sentiment on herding in the context of an emerging market like India. Since the herding behavior is found in almost all the emerging economies, Indian investors may also exhibit the same. The impact of sentiment on herding and its nature needs to be studied as the former has a varying impact on the latter.

4. Data and methodology

To explore and analyze the impact of investor sentiment and herding behavior on the Indian stock market, particularly focusing on the Nifty 50 index, data over the period of 1-4-2015 to 31-3-2024 was considered for the study, and it is divided into three phases, namely Pre-COVID, During the COVID crisis, and the Post-COVID period.
For analysing the results, descriptive statistics, normality test, ordinary least squares, augmented Dickey-Fuller test, etc., are used in Eviews software. In this study, the returns are examined on the basis of the closing prices of the Nifty Index. To examine the presence of herding behavior, Cross Cross-sectional absolute deviation (CSAD) method is used as a herding indicator. For investor sentiment, two proxies-VIX (Volatility Index) and ADR (Advance Decline Ratio) are used.

4.1. Herding indicator

The Cross-Sectional Absolute Deviation (CSAD) measures the extent to which individual stock returns differ from the overall market return. A non-linear relationship between CSAD and market returns indicates the possible presence of herding behavior among investors. To detect the presence of herding, the study relies on the CSAD approach proposed by Chang, Cheng, and Khorana (2000). This model examines whether the dispersion of individual stock returns around the market return decreases during periods of extreme market movements, which is a key indicator of herding.
CSAD Formula;

$$\mathrm{CSADt} = \frac{1}{\mathrm{N}}\sum_{\mathrm{i-1}}^{\mathrm{n}} \quad |\mathrm{Ri,t} - \mathrm{Rm,t}|$$

Where:
Rit is the return of stock i at time t
Rm,t is the market return at time t,
N is the number of stocks.
Regression model to test Herding

CSADt= α+ β1 |Rm,t|+β2 Rm2,t+ εt

According to the CSAD model proposed by Chang, Cheng, and Khorana (2000), if herding is present, the coefficient β2 on the squared market return should be negative and significant. This indicates that as market returns become extreme, dispersion among stock returns decreases — indicating herd behavior.
The Ordinary Least Squares method is used for identifying the presence of the herding effect. R squared, Adjusted R squared, AIC, Absolute market returns and squared market returns, constant values, as well as F-stat and DW statistics are all examined. For CSAD analysis, market returns and individual stock returns of the top 10 companies were used. In this case, the absolute market return and squared market return serve as the independent variables, while cross-sectional absolute deviation serves as the dependent variable.

4.2. Sentiment proxies

Volatility Index (VIX): The Volatility Index (VIX), often referred to as the 'fear gauge,' measures the market's expectation of short-term volatility, typically derived from option prices. A higher VIX value indicates increased market uncertainty or fear, while a lower value suggests investor confidence and market stability. Advance Decline Ratio: The Advance-Decline Ratio (ADR) is a market sentiment indicator that compares the number of stocks that advanced in price to those that declined during a specific period. A higher ADR indicates bullish sentiment, while a lower ADR suggests bearish sentiment among investors.
In this study, Volatility Index (VIX) and Advance Decline Ratio (ADR) were analyzed because they are more quantitative, timely, and broadly accepted. They represent volatility (emotion) and breadth (participation), the two core dimensions of sentiment.

4.3. Relationship between investor sentiment and herding behavior

To understand the relationship between investor sentiment and herding behavior, the following regression equation regarding the ordinary least squares method is used.

β3 sent+εt

Where sent is the investor sentiment variable.
According to Tan et.al (2008), the estimated β3 may take either a positive or a negative value. A negative value indicates a rise in investor sentiment; investors are likely to replicate the decisions of other investors. If investors change their perspective to a pessimistic view

regarding the future, it exhibits herding behavior. On the other hand, a positive value of low investor sentiment indicates a lack of the urge to imitate other investors. This is an indication of reverse herding behavior in the stock market.
A Principal Component Analysis (PCA), which combines proxies into a single index, is used as the Investor Sentiment Index. Converting each variable to the same scale, the Z score is used for standardization. After conversion, composite sentiment is taken as the independent variable.

4.4. Returns

The closing price of the Nifty Index is used for analysing the returns. The data is collected from the National Stock Exchange (NSE). Returns can be calculated by using two methods that is, simple returns and compound returns. The formula for calculating simple return is;

Rt= ((Pt-Pt-1)/Pt-1)*100

Compound returns are calculated as follows;

rt=100%* ln(Pt/Pt-1)

Where, Rt: Simple return at time t
Rt = continuously compounded return at time t
Pt asset price at time t
Ln= natural logarithm

5. Results and discussion

5.1. Descriptive statistics of returns, CSAD, and IS proxies

The following table helps to analyse the various statistical indicators with respect to returns, Cross-Sectional Absolute Deviation (CSAD), and investor sentiment proxies.

Table 1: Descriptive Statistics of Returns, CSAD, and IS Proxies

	NIFTY			CSAD			VIX				ADR		
Phase	P(I)	P(II)	P(III)	P(I)	P(II)	P(III)	P(I)	P(II)	P(III)	D_VIX (III)	P(I)	P(II)	P(III)
Mean	0.0002	0.0004	0.0005	0.0104	0.0118	0.0087	15.430	20.103	15.936	-0.009	1.1734	1.1294	1.1803
Median	0.0002	0.0012	0.0009	0.0095	0.0103	0.0080	15.272	17.432	15.220	-0.057	0.970	0.9050	1.0500
Min	-0.060	-0.139	-0.0489	0.000	0.0000	0.0000	10.447	10.525	10.135	-5.242	0.0400	0.0600	0.0600
Max	0.0331	0.0840	0.0298	0.2459	0.0844	0.0246	28.717	83.607	31.982	7.440	7.1300	12.420	6.3800
S.D	0.0085	0.0137	0.0086	0.0101	0.0068	0.0034	3.0206	9.4847	3.9275	0.879	0.9057	0.9288	0.8266
Skewness	-0.682	-1.698	-0.5442	17.907	4.7070	1.1081	0.9544	3.1598	0.7944	1.222	2.3351	3.947	2.1230
Kurtosis	7.1264	23.864	5.3737	410.15	41.880	4.6006	4.8236	15.897	3.2802	13.97	11.645	35.33	10.030

Source: Computed-Nature of the Data

The three phases of the study are mentioned as
Pre-Covid period - P(I)
During the crisis - P(II)
Post-Covid period - P(III)

Table 2: Results of Unit Root Tests

	NIFTY			CSAD			VIX				ADR		
	P(I)	P(II)	P(III)	P(I)	P(II)	P(III)	P(I)	P(II)	P(III)	D_VIX(III)	P(I)	P(II)	P(III)
ADF	-25.5	-9.13	-26.26	-26.48	-7.805	-11.31	-4.017	-3.411	-2.629	-33.09	-24.45	-21.91	-11.31
P value	0.00	0.00	0.00	0.00	0.00	0.00	0.001	0.000	0.087	0.00	0.00	0.00	0.00

Source: Computed -Results.

The results from the Augmented Dickey-Fuller (ADF) test indicate that Nifty returns, CSAD, and ADR are stationary across all three phases—pre-COVID, during COVID, and post-COVID—as the null hypothesis is rejected. However, in the post-COVID phase, the VIX variable is non-stationary in its level form (ADF test statistic = –2.629), as the test fails to reject the null hypothesis at the 5% level. After taking the first difference, the series becomes stationary, with the ADF test statistic improving significantly to –33.09, and the p-value tends to 0.00, which means the differenced value is highly significant, thereby rejecting the null hypothesis and confirming that the differenced series is stationary.

Table 3: Results of Jarque-Bera Normality Test

	NIFTY			CSAD			VIX			ADR		
	P(I)	P(II)	P(III)	P(I)	P(II)	P(III)	P(I)	P(II)	P(III)	P(I)	P(II)	P(III)
JB	583.18	13796.7	210.551	492083	49610.6	231.385	214.319	6394.81	80.4784	2969.19	34343.8	2025.41
P	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Source: Computed -Results.

Table 4: Regression Output of Herding Effect (2015-2018)

Variable	Coefficient	Standard Error	t-Statistic	p-Value
C (Constant)	0.009380	0.000528	17.77165	0.0000
Absolute Market Return	0.156302	0.061579	2.538238	0.0113
Squared Market Return	0.144906	0.020024	7.236593	0.0000

Source: Computed -Results.

Table 5: Regression Output of Herding Effect (2018-2021)

Variable	Coefficient	Standard Error	T statistic	P value
Constant(c)	0.008961	0.000351	25.53788	0.0000
Absolute Market Return	0.370392	0.039077	9.478521	0.0000
Squared Market Return	-1.567242	0.465164	-3.369223	0.0008

Source: Computed -Results.

Table 6: Regression Output of Herding Effect (2021-2024)

Variable	Coefficient	Standard Error	T statistic	P value
Constant(c)	0.007101	0.000227	31.33448	0.0000
Absolute Market Return	0.294628	0.045346	6.497299	0.0000
Squared Market Return	-3.777873	1.673261	-2.25779	0.0242

Source: Computed -Results.

To examine the presence of herding behavior in the Indian stock market, hypothesis testing was conducted for three periods: pre-COVID, during the COVID crisis, and post-COVID.

According to the CSAD model proposed by Chang, Cheng, and Khorana (2000), if herding is present, the coefficient β2 on the squared market return should be negative and significant. The null hypothesis assumes no herding behavior in the Indian stock market. During the pre-COVID period, the null hypothesis could not be rejected, indicating no evidence of herding as the coefficient β2 of squared market return is positive (0.144906) and significant. However, during the crisis period, the null hypothesis was rejected, showing the presence of herding behavior, as the coefficient β2 of squared market return is negative (-1.567242) and significant. In the post-COVID period, strong evidence of herding was observed as the null hypothesis was again rejected with greater significance because the coefficient shows a huge difference (-3.777873). These results suggest that herding behavior among investors increased during periods of market uncertainty and continued strongly even after the crisis.

Table 7: Regression Results Showing the Presence of Investor Sentiment (2015-2018)

Variable	Coefficient	Standard Error	t-Statistic	p-Value
Constant(c)	0.001592	0.001240	1.283881	0.1996
VIX	-0.000558	7.67E-05	-7.283444	0.0000
ADR	0.006175	0.000256	0.000256	0.0000

Source: Computed -Results.

Table 8: Regression Results Showing the Presence of Investor Sentiment (2018-2021)

Variable	Coefficient	Standard Error	t-Statistic	p-Value
Constant(c)	-0.004928	0.001130	-4.361615	0.0000
VIX	-0.000152	4.61E-05	-3.294321	0.0010
ADR	0.007497	0.000470	15.94095	0.0000

Source: Computed -Results.

Table 9: Regression Results Showing the Presence of Investor Sentiment (2021-2024)

Variable	Coefficient	Standard Error	t-Statistic	p-Value
Constant(c)	-0.004960	0.000404	-12.29084	0.0000
D_VIX	-0.004201	0.000273	-15.38106	0.0000
ADR	0.004633	0.000291	15.94011	0.0000

Source: Computed -Results.

To examine the presence of investor sentiment in the Indian stock market, a regression analysis was conducted. In the pre-COVID phase, as the coefficient of VIX is negative (-0.000558) and statistically significant, it shows an inverse relationship between returns. But during the crisis period, as the coefficient of VIX is negative (-0.000152) and statistically significant, it shows an inverse relationship between returns. And from the post-COVID phase, the independent variable D_VIX represents the first difference of the VIX, capturing the daily change in market volatility. The negative and statistically significant coefficient for D_VIX (-0.0042) indicates that an increase in the change of volatility is associated with a decline in stock returns.

The regression results from the three time periods confirmed the presence of investor sentiment, as the sentiment proxies had a significant impact on stock returns. This indicates that investor mood and behavior influenced the Indian stock market during the study period.

Table 10: Regression Showing the Impact of Sentiment on Herding (2015-2018)

Variable	Coefficient	Standard Error	t-Statistic	p-Value
Constant	0.009472	0.000549	17.24133	0.0000
Absolute market return	0.142148	0.066156	2.148675	0.0320
Squared market return	0.145220	0.020053	7.241834	0.0000
Composite sentiment	0.000323	0.000545	0.592192	0.5539

Source: Computed -Results.

Table 11: Regression Showing the Impact of Sentiment on Herding 2018-2021)

Variable	Coefficient	Standard Error	t-Statistic	p-Value
Constant	0.009316	0.000369	25.25892	0.0000
Absolute market return	0.325711	0.041662	7.817969	0.0000
Squared market return	-1.398610	0.466157	-3.000301	0.0028
Composite sentiment	0.001050	0.000352	2.980271	0.0030

Source: Computed -Results.

Table 12: Regression Showing the Impact of Sentiment on Herding (2021-2024)

Variable	Coefficient	Standard Error	t-Statistic	p-Value
Constant	0.007110	0.000199	35.76535	0.0000
Absolute market return	0.250250	0.024623	10.16310	0.0000
Squared market return	-2.088637	0.738447	-2.828420	0.0048
Composite sentiment	-0.000383	0.000160	-2.384326	0.0174

Source: Computed -Results.

To analyze the impact of investor sentiment on herding behavior, a regression analysis was conducted for three phases: pre-COVID, during the COVID crisis, and post-COVID. During the pre-COVID period, the p-value was not significant, indicating no relationship between investor sentiment and herding behavior. However, during the crisis period, the coefficient for composite sentiment was positive, suggesting that as sentiment increased, reverse herding behavior was observed, where investors moved away from the market consensus. In the post-COVID period, the coefficient for composite sentiment turned negative, indicating that higher investor sentiment led to the presence of herding behavior. Based on these results, it can be concluded that investor sentiment had a varying influence on herding behavior across different market phases, and the null hypothesis of no impact is rejected during the crisis and post-COVID periods.

6. Conclusion

The analysis shows that herding behavior is significantly present in the Indian stock market, particularly during periods of high volatility, as indicated by the significant negative coefficient of the squared return term. Investor sentiment, measured through a composite sentiment index, was found to have a statistically significant negative relationship with CSAD, suggesting that higher sentiment levels increase herding tendencies among investors. The results also show that during extreme market conditions, herding behavior affects stock returns because fundamental values followed by the investors are deviated during extreme market conditions. Additionally, investor sentiment plays a crucial role in determining stock prices, as emotional factors impact stock market movements alongside traditional financial indicators.

This study analyzes the impact of herding behavior and investor sentiment on stock returns in the Indian stock market. By using the Volatility Index (VIX) and the Advance Decline Ratio (ADR), investor sentiment plays an important role in driving market trends. This model highlights how investors tend to follow the crowd, especially during periods of high market volatility, which leads to herding behavior. This collective behavior violates the assumptions of the Efficient Market Hypothesis, contributing to increased volatility and larger fluctuations in stock prices.

The findings of this study emphasize the importance of understanding the behavioral factors that influence the decisions of an investor. By understanding the impact of sentiment and herding behavior, investors and analysts can better manage risks and make informed decisions. The research aims to provide insights into behavioral patterns among investors, particularly during periods of market stress or optimism. This study provides valuable insights into the dynamics of the Indian stock market, suggesting that considering behavioral factors can help improve investment strategies and create a more stable market environment.

7. Economic and policy implications

The noticeable herding behavior and the impact of investor sentiment on stock returns within the Indian equity market suggest they deviate significantly from the efficient market hypothesis. Such behavior suggests that during certain timeframes—especially during periods of excessive market strain—asset values may diverge from actual fundamentals. This behavior causes misvaluation, excessive market volatility, and susceptibility to speculative bubbles and abrupt market corrections. The resulting allocative inefficiencies of capital could lead to misallocation of capital, stunting the most productive economic endeavors, which may have negative implications for the long-term economic growth and stability of the region. Besides, the disproportionate susceptibility of retail investors to sentiment-driven market movements raises concerns regarding the equity of risk and welfare within the financial architecture.

For regulators and policymakers, these results emphasize the importance of enhancing market safeguards and investor education. This includes strengthening real-time surveillance systems to detect herd-driven volatility, calibrating circuit breakers based on sentiment indicators, and conducting financial literacy campaigns to educate on the perils of herd following. Furthermore, promoting stable domestic institutional investment and developing official sentiment indices can help counteract irrational exuberance or panic and build a stronger and more resilient market.

8. Limitations and directions for future research

The study provides valuable insights into herding behavior and investor sentiment, but then certain areas offer scope for improvement. The analysis is based on a nine-year period, which is further divided into three phases. The time period used in the study is informative, but can be extended in future research to understand long-term trends and the trends in different market conditions. In this study, standard estimation methods are used; applying more advanced models has the potential to improve the accuracy and the depth of the findings. For future studies, there are other measures for herding, like Hwang and Salmon (2004) can be used. Additionally, sentiment indicators like Market Mood Index, trading volume, or survey-based indices can offer a more comprehensive understanding of investor sentiment. Advanced econometric models like GARCH and EGARCH may also be useful in finding volatility patterns and market dynamics more effectively.

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Data availability statement

Raw data supporting the findings of this study are available from the corresponding author on request.

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