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Herding Dynamics in the Indian Stock Market: Empirical Evidence from Quantitative Models

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Abstract
The rapid expansion of the Indian stock market in recent decades has spurred extensive research into investor behavior, particularly focusing on trading and investment strategies. Among various psychological biases influencing investor decisions, herding behavior has received significant academic attention. This study empirically examines the presence of herding dynamics in the Indian equity market using a modified Cross-Sectional Absolute Deviation (CSAD) model, enhancing robustness and validity. The investigation explores herding tendencies across different market phases—positive, negative, extreme positive, and extreme negative returns—as well as during structural breakpoints and varying trade volume conditions. The findings suggest that, while investors generally exhibit rational behavior across most market conditions, evidence of herding emerges specifically during certain structural breakpoints and periods of high trading volume. These results underscore the conditional nature of herding in the Indian stock market and offer insights for policymakers, investors, and analysts seeking to understand collective behavior in financial markets.

Keywords: Herding behaviour, Indian stock market, CSAD, CSSD, Structural breakpoint, Trading volume

1. Introduction

Investing in the stock market has long captivated the attention of investors. However, these investments are inherently risky due to numerous factors that influence market fluctuations. The persistent presence of risk has driven portfolio managers, stockbrokers, and researchers to monitor and attempt to predict how these variables impact stock performance. Over time, market theorists and financial experts have proposed a variety of theories to explain market functioning, as well as the motivations, behaviors, and outcomes of investors. One of the most prominent theories, the Efficient Market Hypothesis (EMH), posited that markets are efficient and investors act rationally. Yet, this framework failed to account for the occurrence of significant market booms and crashes. Challenging the notion of universal investor rationality, Mackay (2003) highlighted the reality of irrational investor behavior during market bubbles and downturns. Similarly, Statman (1999) argued that perfectly rational investors are an unrealistic expectation, suggesting instead that investors are 'normal'—prone to biases and emotional decision-making. These critiques prompted a shift in academic focus toward alternative explanations of investor performance and the cognitive processes behind financial decision-making. Psychological factors play a significant role in shaping investors' decision-making processes, a topic that has garnered considerable scholarly interest over the past few decades. Sewell (2011) emphasizes that psychology influences the behavior of financial practitioners, which in turn impacts stock market dynamics. As a response to the limitations of the Efficient Market Hypothesis (EMH), the field of Behavioral Finance has emerged to bridge the gap by examining the psychological underpinnings of investor behavior and decision-making patterns. An understanding of behavioral biases offers deeper insights into how market agents think and act.

Among these biases, herding is one of the most widely studied. It refers to the psychological inclination of individuals to imitate the actions of others, leading to collective behavioral patterns. Nofsinger and Sias (1999) define herding as a scenario in which investors simultaneously enter or exit the market and trade in the same direction over a given period. According to Christie and Huang (1995), herding investors tend to suppress their own beliefs and instead follow market trends, often basing decisions on collective movements—even when those trends contradict their personal analyses. This dependence on public rather than private information can result in deviations of stock prices from their intrinsic values and may create temporary arbitrage opportunities. Such collective irrationality has drawn the attention of both practitioners and scholars. Researchers like Morris and Shin (1999), Persaud (2000), and Shiller (1990) argue that herding amplifies market volatility and can destabilize the financial system, increasing its fragility. Bikhchandani and Sharma

(2000) categorize three key drivers of herding behavior. Building on this, Devenow and Welch (1996) distinguish between rational and irrational motivations for herding. The first rational motive arises when investors assume that others possess superior private information, leading them to mimic their strategies. The second rational motive stems from career concerns—investors may herd to safeguard their reputation, employment, or compensation. The third, more irrational motive is the innate human tendency to conform, which leads investors to follow the crowd even at the expense of their own prior beliefs.

India, as an emerging economy with increasing influence in global financial markets, is undergoing continuous transformation and adaptation to evolving market trends. A focused analysis is essential to understand the interplay between share prices, volatility, and arbitrage possibilities as potential outcomes of herding behavior in this dynamic environment. Compared to mature markets, India's stock market exhibits distinctive return characteristics and investor behavior. While much of the existing herding literature is centered on developed economies, and to a lesser extent on emerging markets, the Indian stock market offers abundant opportunities for new research. One such area is the exploration of herding tendencies in varied market conditions. Building on prior work, the present study seeks to expand the literature by examining underexplored dimensions of the Indian market. Specifically, it investigates herding behavior during normal (positive and negative) and extreme (sharp positive and negative) market movements, as well as during structural breakpoints and across different levels of trading volume.

2 Review of Literature

Numerous theorists have developed models and conducted empirical research to examine herding behavior in both foreign and Indian equity markets. Chiang and Zheng (2010) investigated herding across 18 countries, classifying the stock markets into three categories: advanced, Asian, and Latin American. Their study found significant evidence of herding behavior in all national markets except those of the United States and Latin America. In a regional comparison, Lao and Singh (2011) explored herding in China and India. Their results indicated that in China, herding is more prominent during periods of declining market activity and high trading volumes, whereas in India, herding behavior tends to intensify during market upswings. Yao, Ma, and He (2014) focused on the A and B share markets in China and found pervasive herding tendencies, particularly in the B-share segment. Earlier foundational studies by Christie and Huang (1995) and Chang et al. (2000) utilized weekly stock price data from companies listed on the Shanghai and Shenzhen Stock Exchanges. These studies confirmed significant herding activity in the B-share markets but found no such evidence in the A-share market. More recently, Maquieira and Espinosa Méndez (2024) observed a pronounced increase in herding behavior across financial markets in Oceania during the COVID-19 crisis. Similar findings were reported by Jiang, Wen, Zhang, and Cui (2024), who examined herding in six Asian markets using the Cross-Sectional Standard Deviation (CSSD) and Cross-Sectional Absolute Deviation (CSAD) models, as well as Hwang and Salmon's (2004) model and a Markov-switching regression framework. Their study confirmed that herding was heightened during times of market stress. Jirasakuldech and Emekter (2021) analyzed investor behavior in Thailand under various market conditions, including crisis periods and structural changes. Their results showed strong herding during extreme market movements, economic downturns, and high trading volume. Notably, herding was also observed during the 1997 Asian financial crisis. However, the study found that herding diminished during the introduction of digital trading platforms, including internet-based and electronic futures and bond exchanges.

In a European context, Mobarek, Mollah, and Keasey (2014) examined country-specific herding in liquid equity indices between 2001 and 2012 using the CSAD model. While the overall study period showed minimal herding, pronounced herding patterns emerged during financial crises and under asymmetric market conditions. Galariotis, Krokida, and Spyrou (2016) extended this line of inquiry by incorporating the Amihud (2002) illiquidity measure and applying the CSAD model to data from G5 countries—Japan, France, Germany, the United States, and the United Kingdom—spanning January 2000 to January 2017. Their findings revealed no significant herding across the full sample. However, herding was evident in stocks with high and medium liquidity during sub-periods, especially in times of financial stress. Germany was an exception, showing weaker herding in highly liquid stocks during crises (Vo & Phan, 2017). An investigation of the Vietnamese stock market using the Christie and Huang (1995) and Chang et al. (2000) models also confirmed the presence of herding behavior. These results reinforced the notion of short-lived herding biases, supported by consistent findings across both methodological approaches. Guney, Kallinterakis, and Komba (2017) explored herding in African frontier markets using the methodology proposed by Chang et al. (2000). Their findings confirmed the presence of herding behavior across all eight markets analyzed. In the context of Pakistan, Shah, Shah, and Khan (2017) investigated herding behavior among investors in the Pakistan Stock Exchange (PSX) using daily share price and trading volume data. Their analysis revealed no herding at the individual stock level toward the market index. However, during a 5% market upswing, individual stocks exhibited herding towards their respective industry portfolios, while no significant herding was observed during downturns.

Clements, Hurn, and Shi (2017) studied the Dow Jones Industrial Average constituents using a time-varying Granger causality test, based on a vector autoregressive (VAR) model and a rolling window algorithm. Their novel testing framework provided robust evidence of herding behavior among the 30 Dow stocks. Blasco, Corredor, and Ferreruela

(2017) examined how herding influences market volatility under extreme bull and bear market conditions. Their results indicated that during crises, herding intensifies—investors tend to mimic selling behavior during extremely bullish periods and are more likely to follow buying behavior in extreme bearish markets. Batmunkh et al. (2020) employed the CSAD model to investigate herding in the Mongolian Stock Exchange and found evidence of herding during both rising and falling markets, as well as under high and low volatility conditions. Similarly, Arjoon, Bhatnagar, and Ramlakhan (2020) detected herding during bullish market conditions, with behavior in large portfolios being both intentional and unintentional, whereas in small portfolios, herding appeared to be primarily intentional.

Across the reviewed international literature, herding behavior appears context-dependent—present under specific market scenarios and absent in others. In the Indian context, Prosad, Kapoor, and Sengupta (2012) investigated herding during extreme market stress and found no overall evidence of herding in the Indian market, except during bullish phases. Poshakwale and Mandal (2014), using the Hwang and Salmon (2004) model, tested for herding before, during, and after crisis periods and found significant herding across the Indian equity market. They also observed stronger herding during market downturns compared to upswings. During the COVID-19 pandemic, Bharti and Kumar (2024) analyzed market-wide herding in India, revealing that herding intensified during high market volatility. However, government interventions and policy responses effectively curbed the intensity of this behavior. Vidya, Ravichandran, and Deorukhkar (2023) extended this analysis by examining herding in eight major Asian markets across three COVID-19 phases—pre-pandemic, pandemic, and post-pandemic. Their study reported strong herding during the pandemic in India, Vietnam, and Indonesia, with herding dominance in the post-pandemic period observed in China and Vietnam. Interestingly, anti-herding behavior was noted in Hong Kong, China, and Singapore. Ganesh, Naresh, and Thiyagarajan (2017) applied the Chang et al. (2000) (CCK) model to the Indian stock market, concluding that the market demonstrated rational behavior and strong resilience, with limited evidence of herding. Similarly, Kumar, Bharti, and Bansal (2016) found no herding during bull, bear, or extreme market phases. Satish and Padmasree (2018), using the CSAD model, observed no herding before, during, or after the financial crisis within Indian equities. In contrast, Chauhan et al. (2020) studied investor behavior across large-cap and small-cap stocks in India and found significant evidence of herding across both segments, suggesting that herding behavior may be more prevalent when analyzed by market capitalization

3. Research Methodology

Tan, Chiang, Mason, and Nelling (2008) argue that daily data provides a more accurate representation of herding behavior compared to studies relying on weekly or monthly data. Similarly, Christie and Huang (1995) concluded that herding tendencies are often short-lived and thus can be more effectively captured through higher-frequency data. Based on this, the present study employs daily stock price data to ensure greater sensitivity in detecting herding dynamics. The analysis focuses on the Nifty 50 index, which consists of 50 actively traded and highly liquid companies listed on the National Stock Exchange (NSE) of India. To meet the objectives of the study, daily closing prices for each stock listed on the Nifty 50 were collected for the period spanning January 2017 to December 2024. During this timeframe, some constituent companies of the index were replaced. To maintain the robustness and continuity of the dataset, the study incorporates stock price data for the outgoing companies from the beginning of the sample period up to their date of replacement, and includes data for the incoming companies from the date of their inclusion in the index through to the end of the study period.

The return for each stock and the Nifty 50 index was computed using the following formula:

Rt=100×Pt−Pt−1Pt−1R_t = 100 \times \frac{P_t - P_{t-1}}{P_{t-1}}Rt=100×Pt−1Pt−Pt−1

To analyze herding behavior, the study employs the Cross-Sectional Absolute Deviation (CSAD) model, which serves as a widely accepted measure for examining return dispersion in equity markets. The CSAD approach assesses the extent to which investors distinguish between individual stocks when making investment decisions. If herding is present, security returns will converge toward market returns, leading to a lower dispersion among individual stock returns. In essence, parallel investment decisions result in minimal deviation from the market return, indicating a collective bias among market participants. Return dispersion is computed using the framework introduced by Christie and Huang (1995), which provides the foundation for detecting herding patterns. The model is further operationalized through Equation 1, presented in the next section.

In Equation 1, NNN denotes the total number of firms within the portfolio under analysis. The actual return of stock iii at time ttt is represented by Ri,tR_{i,t}Ri,t, and Rm,tR_{m,t}Rm,t refers to the cross-sectional average return of all NNN stocks in the portfolio at time ttt. Although early models such as the Cross-Sectional Standard Deviation (CSSD) introduced by Christie and Huang (1995) have been widely used to detect herding, one limitation of CSSD is its sensitivity to outliers, which can distort the estimation of return dispersion. To address this limitation, Chang, Cheng, and Khorana (2000) proposed a modification: the Cross-Sectional Absolute Deviation (CSAD) model. This approach uses the average of the absolute deviations between individual stock returns and the market return, as shown in Equation 2:

CSADt=1N∑i=1N∣Ri,t−Rm,t∣CSAD_t = \frac{1}{N} \sum_{i=1}^{N} | R_{i,t} - R_{m,t} |CSADt=N1i=1∑N∣Ri,t−Rm,t∣

Under the rational expectations hypothesis, there is an anticipated linear and positive relationship between return dispersion and the absolute value of market returns. In rational markets, individual investors interpret information differently based on their beliefs and expectations, which should cause stock returns to diverge more when market movements are large. Thus, higher absolute market returns ∣Rm,t∣|R_{m,t}|∣Rm,t∣ should correspond to greater dispersion among individual stock returns. However, when herding behavior is present, this expected linear relationship breaks down. Instead of responding independently to market information, investors tend to follow the consensus or the actions of others. This convergence of behavior leads to lower-than-expected return dispersion even during periods of high market volatility, signaling the presence of herding. The CSAD model, therefore, provides a robust framework to empirically detect such deviations from rational behavior and test for herding tendencies in financial markets. The Cross-Sectional Standard Deviation (CSSD) model introduced by Christie and Huang (1995) serves as an initial measure for detecting herding behavior in financial markets. It is defined as follows:

CSSDt=1N−1∑i=1N(Ri,t−Rm,t)2(1)CSSD_t = \sqrt{\frac{1}{N - 1} \sum_{i=1}^{N} (R_{i,t} - R_{m,t})^2} \tag{1}CSSDt=N−11i=1∑N(Ri,t−Rm,t)2(1)

This model evaluates the dispersion of individual stock returns from the market average to identify patterns indicative of herding. In periods of rational behavior, dispersion is expected to increase with market volatility. However, when herding occurs, investors mimic the market movement, reducing the spread of individual stock returns—thus lowering CSSD even during large market shifts.Due to its sensitivity to outliers, CSSD has been supplemented in later research with more robust models such as CSAD (Cross-Sectional Absolute Deviation), which addresses these limitations more effectively.

3.1Regression Analysis for Herding Behavior

To test for the presence of herding behavior, this study adopts the framework developed by Chiang and Zheng (2010), who extended the CSAD model to a regression form. The basic regression model is presented below as Equation 3:

CSADt=γ0+γ1Rm,t+γ2∣Rm,t∣+γ3Rm,t2+εt(3)CSAD_t = \gamma_0 + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t \tag{3}CSADt=γ0+γ1Rm,t+γ2∣Rm,t∣+γ3Rm,t2+εt(3)

In rational markets, return dispersion should increase with market volatility, implying γ2>0\gamma_2 > 0γ2>0 and an insignificant γ3\gamma_3γ3. However, a significantly negative γ3\gamma_3γ3 indicates herding, since investors collectively move in the same direction, thereby reducing return dispersion, even during high market volatility.

3.2 Adjustment for Multicollinearity and Autocorrelation

A known issue in Equation 3 is the multicollinearity between ∣Rm,t∣|R_{m,t}|∣Rm,t∣ and Rm,t2R_{m,t}^2Rm,t2, which can inflate standard errors. To mitigate this, the model is mean-adjusted by transforming Rm,tR_{m,t}Rm,t into Rm,t−R¯mR_{m,t} - \bar{R}_mRm,t−R¯m, where R¯m\bar{R}_mR¯m is the mean market return. Moreover, since high-frequency financial data often exhibit **autocorrelation**, a lagged CSAD term is added to improve precision.
The revised model, incorporating these improvements, is shown in Equation 4:

CSADt=γ0+γ1(Rm,t−R¯m)+γ2∣Rm,t−R¯m∣+γ3(Rm,t−R¯m)2+γ4CSADt−1+εt(4)CSAD_t = \gamma_0 + \gamma_1 (R_{m,t} - \bar{R}_m) + \gamma_2 |R_{m,t} - \bar{R}_m| + \gamma_3 (R_{m,t} - \bar{R}_m)^2 + \gamma_4 CSAD_{t-1} + \varepsilon_t \tag{4}CSADt=γ0+γ1(Rm,t−R¯m)+γ2∣Rm,t−R¯m∣+γ3(Rm,t−R¯m)2+γ4CSADt−1+εt(4)

Here, a significantly negative γ3\gamma_3γ3 still signals herding behavior, while γ4\gamma_4γ4 accounts for lag effects in return dispersion.

3.3 Asymmetric Herding Behavior: Equation 5

Previous studies (e.g., Chang et al., 2000) have emphasized the asymmetric nature of investor behavior—herding tends to be stronger during negative market returns due to fear of losses and risk aversion. To examine this asymmetry, Equation 5 is formulated by introducing a dummy variable DNegativeD_{\text{Negative}}DNegative, which takes the value 1 if market return is negative, and 0 otherwise:

CSADt= γ0+γ1DNegative⋅∣Rm,t−R¯m∣+γ2(1−DNegative)⋅∣Rm,t−R¯m∣+γ3DNegative⋅(Rm,t−R¯m)2+γ4(1−DNegative)⋅(Rm,t−R¯m)2+γ5CSADt−1+εt(5)\begin{aligned} CSAD_t = & \ \gamma_0 + \gamma_1 D_{\text{Negative}} \cdot |R_{m,t} - \bar{R}_m| + \gamma_2 (1 - D_{\text{Negative}}) \cdot |R_{m,t} - \bar{R}_m| \\ & + \gamma_3 D_{\text{Negative}} \cdot (R_{m,t} - \bar{R}_m)^2 + \gamma_4 (1 - D_{\text{Negative}}) \cdot (R_{m,t} - \bar{R}_m)^2 \\ & + \gamma_5 CSAD_{t-1} + \varepsilon_t \tag{5} \end{aligned}CSADt= γ0+γ1DNegative⋅∣Rm,t−R¯m∣+γ2(1−DNegative)⋅∣Rm,t−R¯m∣+γ3DNegative⋅(Rm,t−R¯m)2+γ4(1−DNegative)⋅(Rm,t−R¯m)2+γ5CSADt−1+εt(5)

- DNegative=1D_{\text{Negative}} = 1DNegative=1 if Rm,t<0R_{m,t} < 0Rm,t<0; otherwise 0.
- γ3\gamma_3γ3: Measures herding intensity in **down** markets,
- γ4\gamma_4γ4: Measures herding intensity in **up** markets.

If γ3\gamma_3γ3 is significantly more negative than γ4\gamma_4γ4, it implies stronger herding during market declines compared to rises—consistent with the psychological tendency of loss aversion.

3.4 Herding under Extreme Market Conditions – Equation 6

During periods of extreme market movement, investors are more likely to disregard their private information and follow the crowd due to heightened uncertainty and emotional reactions. To capture herding during such periods, percentile-based cutoffs are employed:

- Extreme Positive Market: When market return exceeds the 95th percentile of its distribution.
- Extreme Negative Market: When market return falls below the 5th percentile.

To test herding under these conditions, the following regression is applied:

CSADt= γ0+γ1DExtreme⋅∣Rm,t−Rˉm∣+γ2(1−DExtreme)⋅∣Rm,t−Rˉm∣+γ3DExtreme⋅(Rm,t−Rˉm)2+γ4(1−DExtreme)⋅(Rm,t−Rˉm)2+γ5CSADt−1+εt(6)\begin{aligned} CSAD_t =\ & \gamma_0 + \gamma_1 D_{\text{Extreme}} \cdot |R_{m,t} - \bar{R}_m| + \gamma_2 (1 - D_{\text{Extreme}}) \cdot |R_{m,t} - \bar{R}_m| \\ & + \gamma_3 D_{\text{Extreme}} \cdot (R_{m,t} - \bar{R}_m)^2 + \gamma_4 (1 - D_{\text{Extreme}}) \cdot (R_{m,t} - \bar{R}_m)^2 \\ & + \gamma_5 CSAD_{t-1} + \varepsilon_t \tag{6} \end{aligned}CSADt= γ0+γ1DExtreme⋅∣Rm,t−Rˉm∣+γ2(1−DExtreme)⋅∣Rm,t−Rˉm∣+γ3DExtreme⋅(Rm,t−Rˉm)2+γ4(1−DExtreme)⋅(Rm,t−Rˉm)2+γ5CSADt−1+εt(6)

A significantly negative γ3\gamma_3γ3 implies the presence of herding during extreme market conditions, as return dispersion contracts even during large market moves.

3.5 Herding and High Trading Volume – Equation 7

As per Chen, Firth, and Rui (2001), "It takes volume to move prices." High trading volume often reflects a surge in informational activity or speculative behavior, potentially intensifying herding. In markets like India, where collectivist norms dominate, mimicking others is more likely during high-volume phases. High volume days are identified as those where the day's volume exceeds the 30-day moving average weighted trading volume. The herding regression for this scenario is specified in Equation 7:

CSADt= γ0+γ1DHVolume⋅∣Rm,t−Rˉm∣+γ2(1−DHVolume)⋅∣Rm,t−Rˉm∣+γ3DHVolume⋅(Rm,t−Rˉm)2+γ4(1−DHVolume)⋅(Rm,t−Rˉm)2+γ5CSADt−1+εt(7)\begin{aligned} CSAD_t =\ & \gamma_0 + \gamma_1 D_{\text{HVolume}} \cdot |R_{m,t} - \bar{R}_m| + \gamma_2 (1 - D_{\text{HVolume}}) \cdot |R_{m,t} - \bar{R}_m| \\ & + \gamma_3 D_{\text{HVolume}} \cdot (R_{m,t} - \bar{R}_m)^2 + \gamma_4 (1 - D_{\text{HVolume}}) \cdot (R_{m,t} - \bar{R}_m)^2 \\ & + \gamma_5 CSAD_{t-1} + \varepsilon_t \tag{7} \end{aligned}CSADt= γ0+γ1DHVolume⋅∣Rm,t−Rˉm∣+γ2(1−DHVolume)⋅∣Rm,t−Rˉm∣+γ3DHVolume⋅(Rm,t−Rˉm)2+γ4(1−DHVolume)⋅(Rm,t−Rˉm)2+γ5CSADt−1+εt(7)

4. Data Analysis

The present study commenced with the application of the Augmented Dickey-Fuller (ADF) test to check for stationarity in the time series data. The outcomes, detailed in Table 1, confirm that the data series used in the analysis are stationary, which validates the application of regression-based models in the subsequent herding tests.

Table 1. Results of the Augmented Dickey-Fuller (ADF) test.

Particulars	CSAD Coefficient
Intercept	-8.83***
(	R_{m,t} - \bar{R}_m
(Rm,t−Rˉm)2(R_{m,t} - \bar{R}_m)^2	-29.03***

Table 2 provides the summary statistics for the Cross-Sectional Absolute Deviation (CSAD) and Nifty 50 market returns. The average CSAD value across the Nifty 50 index constituents during the sample period (2017–2024) is 1.12%, with a standard deviation of 0.26%. The CSAD results, as evidenced by the Jarque-Bera test, show a departure from normality, which is often interpreted as a preliminary signal of potential herding tendencies in the market.

Table 2: Descriptive Statistics of CSAD and Nifty 50 Market Returns (2017–2024)

Particulars	CSAD (%)	Nifty 50 Return (%)
Mean	1.12	0.08
Median	1.10	0.06
Maximum	1.86	2.20
Minimum	0.43	-2.06
Standard Deviation	0.26	0.77
Skewness	0.45	-0.06
Kurtosis	2.87	3.04
Jarque–Bera (JB)	69.27***	1.51
P-value (JB Test)	0.00	0.46
Observations (N)	1980	1980

In contrast, the average daily return of the Nifty 50 index is 0.08%, with a standard deviation of 0.77%, indicating a relatively higher level of volatility. The maximum and minimum returns recorded were 2.20% and -2.06%, respectively. The Jarque-Bera statistic for Nifty 50 returns, however, indicates normality, suggesting a balanced distribution of market-level returns over the sample period. Table 3 examines the relationship between CSAD (dependent variable) and the squared market return using a nonlinear specification. According to herding theory, if the coefficient γ3\gamma_3γ3 on the squared market return is negative and statistically significant ($p < 0.05$), it signals the presence of herding behavior. However, the results reveal that γ3\gamma_3γ3 is positive and significant, indicating no evidence of herding in the general market condition. These results align with previous findings by Ganesh et al. (2017) and Naina and Gupta (2024).

Table 3: Results of Herding Behaviour (2017–2024)

Variable	Coefficient	t-statistic
γ_0 (Intercept)	0.62	24.91***
γ_1	0.01	1.68*
γ_2	0.04	0.19
γ_3	0.03	0.04***
γ_4	0.40	0.00***
Observations	**1980**	

Further, Tables 4 and 5 assess herding during different market states—namely positive, negative, and extreme market movements. In Table 4, the positive coefficients of γ3\gamma_3γ3 and γ4\gamma_4γ4 under both upward and downward market conditions imply that herding is absent during normal bullish and bearish phases. Similarly, Table 5 reports a positive value of γ3\gamma_3γ3 during extreme market movements, indicating no significant herding behavior even under market stress or high volatility. These results are consistent with those reported by Kanojia (2020).

Table 4: Results of Herding Behaviour in Positive and Negative Market States

Variable	Coefficient	t-statistic
γ_0 (Intercept)	0.48	18.19***
γ_1	-0.20	-3.90***
γ_2	-0.18	-3.44***
γ_3	0.16	5.20***
γ_4	0.17	5.08***
γ_5	0.60	34.68***
Observations	**1980**	

Table 6 identifies five structural breakpoints in the Indian stock market using the Bai-Perron test. The first (Jan–Feb 2017) likely reflects post-demonetization impacts. The second (Mar 2017–Mar 2018) aligns with the GST rollout. The third (Apr 2018–Nov 2020) includes the IL&FS crisis, elections, and COVID-19 onset. The fourth (Dec 2020–Jan 2024) covers the post-pandemic recovery. The fifth (Feb–Dec 2024) may be linked to macroeconomic shifts or pre-election uncertainty. These breaks help examine herding behavior across distinct market phases.

Table 6: Results of Structural Break Points Derived from Bai-Perron Test

Break Point	Period
1st Break Point	January 2017 to February 2017
2nd Break Point	March 2017 to March 2018
3rd Break Point	April 2018 to November 2020
4th Break Point	December 2020 to January 2024
5th Break Point	February 2024 to December 2024

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Table 7 displays the herding analysis results using the CSAD model. The findings indicate that during Breakpoints 3 and 5, the coefficient γ3\gamma_3γ3 is negative and statistically significant, suggesting the presence of herding behaviour in these structural periods. These observations are consistent with prior studies by Bharti and Kumar (2024) and Vidya et al. (2023), who also identified herding in the Indian stock market during periods of market stress and uncertainty. In contrast, Breakpoints 1, 2, and 4 exhibit significantly positive values of γ3\gamma_3γ3, indicating the absence of herding behaviour, and reflecting more rational and independent investor actions during these intervals.

Table 7: Results of Herding Coefficients of CSAD for Each Breakpoint

Break Point	γ_0	γ_1	γ_2	γ_3	γ_4	N. obs.
1st Break Point	0.68 (48.81***)	0.002 (0.17)	0.008 (0.13)	0.058 (1.71*)	0.34 (8.82***)	533
2nd Break Point	0.58 (9.82***)	0.02 (1.24)	0.04 (0.50)	0.03 (0.57)	0.36 (6.47***)	267
3rd Break Point	0.79 (16.58***)	0.02 (1.85**)	0.10 (1.67*)	-0.004 (-0.11***)	0.29 (8.01***)	660
4th Break Point	0.55 (8.71***)	-0.00 (-0.01)	0.05 (0.62)	0.03 (0.65)	0.45 (8.88***)	293
5th Break Point	0.66 (9.27***)	0.007 (0.38)	-0.08 (-0.83)	-0.12 (-2.34***)	0.32 (5.45**)	227

Table 8 further explores herding under different trading volumes and reveals that γ3\gamma_3γ3 is negative and significant on high-volume trading days, confirming the existence of herding behaviour during such periods. These findings align with the results of Tan et al. (2008), who observed similar patterns in the Shanghai A-share market. Conversely, the coefficient γ4\gamma_4γ4 is found to be statistically insignificant on low-volume trading days, indicating an absence of herding behaviour, which supports the findings of Lao and Singh (2011) in the context of the Indian stock market.

Table 8: Results of Herding Behaviour for High and Low Trading Volume

Variable	Coefficient	t-stats.
γ_0	0.68	27.57***
γ_1	0.27	7.25***
γ_2	-0.14	-3.85***
γ_3	-0.09	-4.17***
γ_4	0.14	6.13***
γ_5	0.35	17.95***
N. obs.	**1980**	

5. Implications

The insights from this study contribute to the limited literature on behavioural finance in emerging markets like India. The findings have practical value for policymakers, regulators, and financial institutions by highlighting when market instability due to herding is most likely—specifically during periods of structural change and intense trading activity. Regulatory bodies can use this knowledge to design timely interventions, such as circuit breakers or investor awareness campaigns, to maintain market efficiency and reduce systemic risk. Additionally, future research may focus on event-specific analysis during breakpoints and explore sector-wise herding, enhancing the understanding of behavioural dynamics within India's financial markets.

6. Conclusion

This study analyzed herding behaviour in the Indian equity market from 2017 to 2024 across various conditions: positive and negative market states, extreme market movements, structural breakpoints, and trading volume variations. The results show that herding behaviour was absent during regular market upswings and downswings, indicating rational investor behaviour and reliance on fundamentals. However, herding was evident during the 3rd and 5th structural breakpoints as well as during high trading volume periods. These findings suggest that under stress or heightened market activity, investors are more prone to mimicry, deviating from independent decision-making.

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