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HERDING BEHAVIOR IN EMERGING AND DEVELOPED MARKETS: EVIDENCE FROM INDIA AND THE UNITED STATES DURING THE COVID-19 CRISIS

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Abstract

Purpose – This study investigates the presence of herding behavior in India and the U.S. during the COVID-19 crisis, offering comparative evidence from an emerging and a developed market during a period of global financial stress.

Methodology/approach – The analysis uses daily, weekly and monthly closing price data of individual stock from the BSE 500 and S&P 500 markets during the COVID-19 period and employs the CSAD and CSSD frameworks of Christie and Huang (1995) and Chang et al. (2000) to detect herding during periods of intense market movements.

Findings – The analysis shows that herding is present only in the U.S. stock market during extreme upward movements in both daily and weekly data, while no significant herding behavior is observed in the Indian market during the COVID-19 period.

Implications – The presence of herding only in the U.S. market during extreme upswings indicates greater synchronized trading under stress, while India shows more diverse investor behavior. These results highlight the need for market regulators in both countries to closely monitor investor behavior during periods of heightened uncertainty to ensure stability, protect retail participants, and strengthen market resilience during future crises.

Keywords: Herding Behavior, Covid-19, Emerging and Developed Market, India and U.S.
JEL Codes: D53, F65, G01, G15 and G41

Introduction

Herding has long been recognized as an inherent part of human behavior, rooted in early social instincts to follow group actions during times of uncertainty. While early social psychologists described herd behavior as impulsive and irrational crowd responses, later research suggests that conformity often reflects a psychological need for assurance when individuals face ambiguous situations, Rook (2006). In financial markets, these tendencies become particularly significant, as investors may overlook their own assessments and instead follow market trends, a pattern that challenges the assumptions of the Efficient Market Hypothesis, Fama (1970). Under such behavior, prices may deviate from fundamental values because decisions are shaped more by imitation than by information, Chang et al., (2000).

Herding behavior has become a central theme in behavioral finance, reflecting the idea that investors often rely on collective actions rather than independent judgment when making financial decisions. Early work by Devenow and Welch (1996) emphasizes that such imitation occurs because investors frequently face uncertainty about market fundamentals and the quality of available information. When investors perceive others as better informed, they may abandon their own signals to follow the crowd, a phenomenon that challenges the assumption of fully rational behavior embedded in traditional market theories, Fama (1970). The tendency to imitate becomes particularly strong during episodes of heightened uncertainty, when the cost of making incorrect decisions becomes substantial, Bikhchandani & Sharma (2000).

Differences between developed and emerging markets add another layer of complexity to understanding herding behavior. Developed markets generally benefit from stronger regulatory frameworks, greater information transparency, and a higher share of institutional investors, which can moderate irrational crowding. Nevertheless, research shows that institutional investors in these markets may still engage in coordinated trading due to reputational concerns or performance comparisons, Scharfstein & Stein (1990). On the other hand, emerging markets often experience information asymmetries, retail-investor dominance, and weaker regulatory mechanisms, making them more vulnerable to herd-driven dynamics, Tan et al., (2008). Empirical evidence from India reinforces this pattern, as studies document stronger herding during periods of heightened volatility and major economic disruptions, Garg & Kumar (2018). The COVID-19 pandemic provides an important setting for examining herding, as the crisis created extreme uncertainty, rapid information flows, and sharp market fluctuations worldwide. Such environments often intensify investors' reliance on collective signals rather than private analysis. Although developed markets like the United States typically exhibit stronger regulatory structures and higher institutional participation, their investors are not immune to behavioral biases during periods of severe stress, Nofsinger & Sias (1999). Emerging markets such as India, characterized by greater information asymmetry and a larger share of retail participants, tend to experience stronger herding pressures during volatile conditions, Lakshman et al. (2013).

Despite extensive literature on herding, comparative analysis between emerging and developed markets during global crises remains limited. This study aims to fill that gap by examining herding behavior in the Indian and U.S. stock markets during the COVID-19 period. The remainder of the paper is organized as follows: the next part reviews the existing literature on herding behavior, followed by a description of the data and research methodology. This is then followed by a discussion of the empirical findings, and the paper closes with concluding observations.

Literature Review

Herding behavior in financial markets is often difficult to separate from normal market movements. Devenow and Welch (1996) explain that the main challenge lies in distinguishing spurious herding, which occurs when investors imitate others without sharing the same information, from intentional herding, where investors follow others to protect their reputation rather than based on informed judgment. According to Caparrelli et al. (2004) , this intentional imitation can cause investors to disregard their own information and abandon rational decision-making.

From a theoretical perspective, herding is generally classified as either rational or irrational. Rational herding occurs when investors intentionally follow more experienced or better-informed market participants to maintain their reputation or avoid being blamed for poor performance. Scharfstein and Stein (1990) argue that fund managers herd because their performance is judged relative to peers, making imitation a way to share potential blame, while Devenow and Welch (1996) suggest that money managers mimic benchmark portfolios to avoid appearing less skilled. Bikhchandani and Sharma (2000) add that information cascades arise when investors ignore their own signals and rely on others' actions.

In contrast, irrational herding refers to situations where investors disregard their private information and simply follow the crowd. Christie and Huang (1995) describe this as conformity to market consensus even when investors disagree with expected outcomes, and Chang et al. (2000) attribute it to psychological biases rather than rational decision-making. Nofsinger and Sias (1999) further show that institutional investors may herd through positive feedback trading even when they do not possess superior information, highlighting the behavioral nature of irrational herding.

In emerging markets, herding is more pronounced due to weaker market structures and informational inefficiencies. Studies on countries such as South Korea, Taiwan, and China indicate that factors like limited information availability, policy interventions, and the dominance of retail traders make coordinated investor behavior more likely (Chang et al., (2000); Tan et al., (2008); Chiang et al., (2010). Lakshman et al., (2013) find that collective market movements become more pronounced when the market is under stress. Garg et al., (2018) show that herding intensifies during volatile phases, while Samal (2024) notes that major economic events amplify this behavior.

Empirical findings on herding in developed markets are mixed. According to Nofsinger and Sias (1999), institutional investors in the U.S. often make similar trading decisions, reflecting clear herding behavior. In contrast, Christie and Huang (1995) and Chang et al. (2000) notice that markets such as Japan, Hong Kong, and U.S.A do not exhibit strong herding tendencies, since stock returns tend to spread out rather than cluster during periods of sharp market fluctuations. In Japan, both institutional and individual investors tend to make similar trading decisions, whereas foreign investors depend more on their private information rather than following the crowd, as noted by Iihara et al. (2001). Chiang and Zheng (2010) further detect herding in several developed Asian markets but find it largely absent in Latin America.

Recent literature from 2020 onward has expanded the understanding of herding in the context of crises, behavioral drivers, and digital platforms. Lodha and Soral (2020) concludes that both Indian and U.S. markets show no significant herding during 2013–2018, and Indian investors do not follow the trading behavior of U.S. investors. Moreover, Herding intensified during the COVID-19 pandemic in both developed and emerging markets, with economic uncertainty amplifying imitation behavior, Tan (2023); Ahn et al., (2024). Overall, earlier studies indicate that herding is typically limited in developed markets such as the U.S., while it is more prominent in emerging markets like India, especially during volatile periods. Yet, evidence on herding during global crises such as COVID-19 remains inconsistent. This study contributes by comparing the behavior of India and the U.S. during the pandemic, offering insights into herding patterns across two contrasting market environments.

Data and Methodology

Data

The study analyzes herding behavior during COVID-19 using data from January 1, 2019 to December 31, 2023. It focuses on the S&P 500 (US) and BSE 500 (India), chosen for their broad market coverage. Stock prices for all index constituents were obtained from Yahoo Finance and returns at monthly, weekly, and daily frequencies were generated to capture diverse investor horizons. The dataset includes 1,258 daily, 261 weekly, and 60 monthly observations for the S&P 500, and 1,158 daily, 247 weekly, and 58 monthly observations for the BSE 500, providing a comprehensive view of market behaviour throughout the pandemic.

Methodology

Following the first approach, Lakonishok, Shleifer, and Vishny (1991) introduced a model to measure herding by assessing whether fund managers tend to trade the same stock at the same time rather than independently. However, since detailed trading data of institutional investors is not readily available in the Indian context, this study adopts a market-wide approach, employing the models of Christie and Huang (1995) and Chang et al. (2000) to examine herding behaviour in the Indian and U.S. markets during the COVID-19 crisis.

Christie and Huang (1995) developed the first methodology for identifying market-wide herding, suggesting that when investors move in the same direction, the dispersion of individual stock returns diminishes. Moreover, Chang et al. (2000) introduced the CSAD measure to detect herding by evaluating the dispersion between individual stock returns and the overall market return. According to Tan et al., (2008) under rational pricing, CSAD should increase linearly with market returns but during herding this relationship becomes non-linear and weaker. To further distinguish between intentional and unintentional herding, Hwang and Salmon (2001) examined cross-sectional variation in stock betas.

To capture herd behavior, CH (1995) proposed measuring return dispersion using the Cross-Sectional Standard Deviation (CSSD) of individual stock returns relative to the market.

$$CSSD_t = \sqrt{\frac{\sum_{i=1}^{N}(R_{i,t}-R_{m,t})^2}{N-1}} \quad ....(1)$$

Where $R_{i,t}$ represents the return of stock i at time t, and $R_{m,t}$ denotes the average return of all N stocks in the market at that same time.

Christie and Huang (1995) noted that herding becomes more common during extreme market movements. This assumption is examined using the following equations:

$CSSD_t = \alpha + \beta_1 D_t^L + \beta_2 D_t^U + e_t$
....(2)

The coefficient α reflects average dispersion under normal market conditions. The dummy variables D_t^L and D_t^U take the value 1 when returns fall into the lower or upper extreme tails, and 0 otherwise. In this model, significantly negative β_1 or β_2 indicates herding. Extreme market movements are identified using the 1%, 2%, and 5% return tails.

This study also employs the CSAD measure to capture return dispersion, following the approach of Tan et al. (2008). The calculation of CSAD is presented in Eq. (3):

$CSAD_t = \frac{1}{N}\sum_{i=1}^{N}\left[R_{i,t} - R_{m,t}\right]$
....(3)
$CSAD_t = \alpha + \gamma_1 \left|R_{m,t}\right| + \gamma_2 R_{m,t}^2 + e_t$ ....(4)

Where, $\left|R_{m,t}\right|$ is the average return of the equal-weighted market portfolio at time t, representing the market return. γ_1 is the coefficient for $\left|R_{m,t}\right|$, while $R_{m,t}^2$ is its squared term, with γ_2 as its coefficient.
Herding may differ in rising versus falling markets, so positive and negative returns are examined separately. Since market stress can amplify herding (Tan et al., 2008), the following equations test these asymmetric effects:

$CSAD_t^{UP} = \alpha + \gamma_1^{UP}\left|R_{m,t}^{UP}\right| + \gamma_2^{UP} R^{2}{}_{m,t}^{UP} + \varepsilon_t , R_{m,t} > 0$ ....(5)

$CSAD_t^{DOWN} = \alpha + \gamma_1^{DOWN}\left|R_{m,t}^{DOWN}\right| + \gamma_2^{DOWN} R^{2}{}_{m,t}^{DOWN} + \varepsilon_t , R_{m,t} < 0$ ....(6)

$R_{m,t}^{UP}$ represents the market return when the market is rising, and $R^{2}{}_{m,t}^{UP}$ is its squared term. $CSAD_t^{UP}$ is the CSAD at time t that satisfies $R_{m,t}^{UP}$.. The same notation with a "down" superscript applies when the market is falling. Absolute values of $\left|R_{m,t}^{UP}\right|$ and $\left|R_{m,t}^{DOWN}\right|$ are used to compare the linear coefficients in Eqs. (5) and (6). A market return above zero indicates a rising market; otherwise, it is classified as falling.

Since herding is more likely during extreme market conditions, the CCK model is applied to test herding under exceptionally high and low return periods using the following equations:

$CSAD_t^{UP} = \alpha + \gamma_1^{UP}\left|R_{m,t}^{UP}\right| * D_t^U + \gamma_2^{UP} R^{2}{}_{m,t}^{UP} * D_t^U + \varepsilon_t \quad , \quad R_{m,t} > 0$
....(7)

$CSAD_t^{DOWN} = \alpha + \gamma_1^{DOWN}\left|R_{m,t}^{DOWN}\right| * D_t^L + \gamma_2^{DOWN} R^{2}{}_{m,t}^{DOWN} * D_t^L + \varepsilon_t \quad , \quad R_{m,t} < 0$
....(8)

D_t^U=1 when the market return on day *t* falls in the extreme upper tail, and D_t^L=1 when it falls in the extreme lower tail; otherwise, both equal 0. The upper and lower tails are defined using the 1%, 5%, and 10% cut-off points of the return distribution.

Several researchers, including Lao and Singh (2011), have examined herding during normal market conditions. To identify herding in these periods of regular returns, the study applies the following empirical models:

$$\mathrm{CSAD}_t^{\mathrm{Normal}} = \alpha + \gamma_1 |\mathrm{R}_{m,t}| \times N_t + \gamma_2 \mathrm{R}_{m,t}^2 \times N_t + \varepsilon_t \, , N_t = 1 \quad \text{....(9)}$$

γ_1 represents the coefficient for $|\mathrm{R}_{m,t}|$, while γ_2 is the coefficient for $\mathrm{R}_{m,t}^2$. N_t = 1 when the market return on day t lies outside the extreme upper and lower tails, and 0 otherwise. Significance levels are indicated at 1%, 5%, and 10%.

To assess the robustness of the results and the impact of the COVID-19 crisis on herding, the CCK model is applied to three sub-sample periods: the pre-pandemic phase (Jan 1, 2019–Dec 31, 2019), the pandemic shock and high-uncertainty period (Jan 1, 2020–Jun 30, 2021), and the post-pandemic recovery phase (Jul 1, 2021–Dec 31, 2023).

Additionally, to ensure the stationarity of time series data, the Augmented Dickey-Fuller test is employed. Further, the Jarque-Bera test, Durbin-Watson Test, and ARCH LM test are run to inspect the error terms for normality, autocorrelation, and heteroskedasticity. These issues can invalidate the regression results, so corrections are applied. Non-normality is addressed through variable transformations, autocorrelation is reduced by adding lagged dependent variables, and heteroskedasticity is handled using the GARCH(1,1) model. For datasets that are not continuous, where AR and GARCH models cannot be used, Newey–West standard errors are used to correct for both autocorrelation and heteroskedasticity.

Results

Descriptive Statistics

In Table 1, Both markets show positive mean values of CSSD and CSAD, indicating regular cross-sectional return dispersion. The BSE 500 records slightly higher averages than the S&P 500, reflecting greater variability and volatility in the Indian market. Return series for both indices display strong skewness and leptokurtic kurtosis, highlighting non-normal distributions and extreme return movements, especially during the COVID-19 period. The Jarque–Bera test confirms these deviations from normality at all frequencies.

Across both markets, weekly and monthly CSSD and CSAD values exceed daily values, indicating that return dispersion increases with longer time intervals, consistent with earlier studies Tan et al. (2008). Finally, ADF test results indicate that all series—market returns, CSSD, and CSAD are stationary across all frequencies, confirming the suitability of the data for further herding analysis.

Table 1: Descriptive statistics of cross sectional standard deviation (CSSD), cross sectional absolute deviation (CSAD) and maket return ($\mathrm{R}_{m,t}$)

Statistics	S & P 500			BSE 500		
Daily						
	CSSD	CSAD	$R_{m,t}$	CSSD	CSAD	$R_{m,t}$
Mean	0.0171	0.0119	0.0008	0.0227	0.0157	0.0012
Median	0.0158	0.0109	0.0012	0.0212	0.0147	0.0031
Maximum	0.0813	0.0594	0.1143	0.0841	0.0574	0.0549
Minimum	0.0053	0.0039	-0.1271	0.0121	0.0083	-0.0921
SD	0.0068	0.0051	0.0141	0.0068	0.0046	0.0119
Skewness	3.5938	3.9612	-0.5832	3.0321	3.1024	-1.3875
Kurtosis	22.3932	25.6782	15.1421	15.2591	16.2094	8.7294
Sum	21.5631	15.0143	1.0081	26.3383	18.2188	1.4733
Sum Sq. Dev.	0.0586	0.0323	0.2508	0.0537	0.0249	0.1651
Jarque-Bera	22404.1391	30175.7538	7793.0516	9017.6518	10267.9374	1953.7981
Probability	0	0	0	0	0	0
ADF Statistics	-5.8778	-5.8409	-10.6450	-5.6023	-5.1790	-9.6297
P-Value	3.1284e-07	3.7793e-07	4.8203e-19	1.2562e-06	9.7016e-06	2.5826e-09
Conclusion	Stationary	Stationary	Stationary	Stationary	Stationary	Stationary
Weekly						
Mean	0.0375	0.0267	0.0037	0.0519	0.0406	0.0062
Median	0.0345	0.0246	0.0047	0.0472	0.0374	0.0098
Maximum	0.1056	0.0759	0.2042	0.2322	0.1342	0.1045
Minimum	0.0122	0.0089	-0.1618	0.0296	-0.1204	0.0198
SD	0.0131	0.0099	0.0302	0.0186	0.0164	0.0292
Skewness	2.3074	2.5981	0.0821	4.5961	3.1736	-0.6708
Kurtosis	8.0578	9.4877	11.5667	36.4807	12.9292	3.2827
Sum	9.7666	6.9442	0.9722	12.7704	10.0058	1.5428
Sum Sq. Dev.	0.0451	0.0257	0.2371	0.0854	0.0665	0.2099
Jarque-Bera	507.8539	748.4801	795.3414	12355.9316	1423.4988	19.2725
Probability	5.259E-111	2.9485E-163	1.9669E-173	0	0	6.5316E-05
ADF Statistics	-2.9389	-3.6046	-8.7413	-4.6521	-3.8313	-13.2807
P-Value	0.0410	0.0056	3.0029e-14	0.0002	0.0026	7.7028e-25

Conclusion	Stationary	Stationary	Stationary	Stationary	Stationary	Stationary
Monthly						
Mean	0.0777	0.0571	0.0146	0.0002	0.0794	0.0288
Median	0.0731	0.0548	0.0151	-0.0019	0.0757	0.0334
Maximum	0.1592	0.1161	0.1487	0.0915	0.1385	0.1754
Minimum	0.0536	0.0386	-0.1691	-0.0914	0.0553	-0.2778
SD	0.0207	0.0143	0.0584	0.0361	0.0191	0.0709
Skewness	2.2972	1.9703	-0.3209	0.1873	1.6149	-1.1854
Kurtosis	6.6928	5.1851	0.8766	0.9561	2.6401	5.2154
Sum	4.5869	3.3631	0.8637	0.0131	4.5277	1.6471
Sum Sq. Dev.	0.0249	0.0118	0.1983	0.0719	0.0204	0.2822
Jarque-Bera	85.4166	49.9119	12.0971	10.0742	25.0857	25.0081
Probability	2.8313E-19	1.4512E-11	0.0023	0.0064	3.5702E-06	3.7117E-06
ADF Statistics	-5.8517	-6.5613	-6.7751	-7.3391	-3.1649	-7.4508
P-Value	3.5754e-07	8.3654e-09	2.5826e-09	1.0769e-10	0.0221	5.6753e-11
Concusion	Stationary	Stationary	Stationary	Stationary	Stationary	Stationary

This table presents the descriptive statistics of daily, weekly, and monthly returns, along with CSSD and CSAD measures, for the S&P 500 (Standard and Poor's 500) and BSE 500 (Bombay Stock Exchange Top 500) over the period January 2019 to December 2023.

Empirical results

Table 2 presents the regression estimates based on the Christie and Huang (1995) daily, weekly and monthly data under different tail-cutoff criteria, and the overall evidence shows no signs of herding in either market. For both indices, the daily and weekly results reveal that all β_1 and β_2 coefficients are positive and mostly statistically significant, indicating that return dispersion increases during extreme upward and downward market movements rather than decreases, which contradicts the presence of herding. Monthly results show a similar pattern for the S&P 500, while the BSE 500 coefficients are mostly insignificant but still do not display the negative relationship required to support herding. Across all frequencies, the coefficient magnitudes are largest under the 1% tail and decline as the cutoff widens, confirming that dispersion responds more strongly to extreme market conditions. Overall, the findings suggest that investors in both markets do not behave in a herding manner during periods of extreme price movements.

Table 2: Regression Results for $CSSD_t$, (CH Model)

	S & P 500			BSE 500		
Daily						
	1%	2%	5%	1%	2%	5%

α	0.0166	0.0164	0.0161	0.0223	0.0221	0.0233
t-statistics	99.6478	97.4788	90.2825	121.6873	118.5134	25.2422
β_1	0.0272	0.0189	0.0125	0.0226	0.0161	-0.0009
t-statistics	16.6502	16.3237	16.2523	12.6174	12.4578	-1.0313
β_2	0.0221	0.0166	0.0091	0.0175	0.0112	0.0054
t-statistics	13.4899	14.3442	11.8322	9.7935	8.7604	4.2548
Adjusted R^2	0.2648	0.2682	0.2336	0.1781	0.1631	0.0406
F-Statistics	227.2814	231.2696	192.4589	126.2751	113.7113	25.5059
Residual Test						
ARCH Test F-Value	145.4592	246.8797	472.8582	7.0165	18.3921	141.7906
Obs*R^2	130.5481	206.5994	343.9062	6.9864	18.1349	126.4921
Durbin Watson Stat.	1.0563	1.0751	1.0441	1.2339	1.1891	0.9785
Weekly						
α	0.0364	0.0359	0.0356	0.0505	0.0502	0.0494
t-statistics	53.7595	51.8487	45.9452	46.9681	45.6681	42.4077
β_1	0.0581	0.0361	0.0197	0.0488	0.0409	0.0269
t-statistics	9.2808	8.0198	5.8332	5.0421	5.3568	5.4561
β_2	0.0424	0.0351	0.0195	0.0608	0.0407	0.0188
t-statistics	6.7654	7.7915	5.7929	6.2743	5.3332	3.8149
Adjusted R^2	0.3315	0.3168	0.1936	0.2021	0.1805	0.1407
F-Statistics	65.2285	61.0713	32.1032	32.0095	27.9891	21.0656
Residual Test						
ARCH Test F-Value	0.00016	0.0083	0.03276	3.1777E-05	0.0154	0.0107
Obs*R^2	0.00016	0.0083	0.03288	3.2038E-05	0.0156	0.0108
Durbin Watson Stat.	2.40702	2.40554	2.34928	1.4155	1.7053	1.6942
Monthly						
α	0.0739	0.0738	0.0736	0.0003	-0.0010	-0.0038
t-statistics	44.3306	37.5854	33.0601	0.0687	-0.2655	-0.7963
β_1	0.0714	0.0715	0.0557	0.0348	0.0540	0.0517
t-statistics	7.9591	6.8182	5.7931	0.9556	2.1265	2.5278
β_2	0.0831	0.0432	0.0254	-0.0407	-0.0111	0.0249
t-statistics	6.6043	4.1267	2.6495	-1.1176	-0.4398	1.2202
Adjusted R^2	0.6384	0.5068	0.3897	0.0036	0.0483	0.0917
F-Statistics	52.2201	30.8096	19.5237	1.1009	2.3958	3.7771
Residual Test						

ARCH Test F-Value	2.0351	1.4972	0.6268	4.0764	2.1082	4.6362
Obs*R^2	2.0338	1.5103	0.6421	3.9281	2.1041	4.4232
Durbin Watson Stat.	2.0202	2.0545	1.6278	2.9501	2.8274	2.8807

This table presents the results of the regression: $CSSD_t = \alpha + \beta_1 D_t^l + \beta_2 D_t^u + e_t$ for the BSE 500 and S&P 500 indices across daily, weekly, and monthly frequencies.Significance levels are indicated at 10%, 5%, and 1%.

Table 3: Regression Results for $CSAD_t$, (CCK Model)

	S & P 500		BSE 500	
Daily				
Mean equation				
α	0.0093	0.0041	0.0132	0.0058
t-statistics	54.7304	17.3638	70.2316	18.1823
γ_1	0.2727	0.1583	0.2771	0.2078
t-statistics	14.6771	10.4754	11.4298	10.6507
γ_2	0.5901	0.4750	1.2638	0.6630
t-statistics	2.4247	2.4901	2.7897	1.8318
AR(1)	-	0.5338	-	0.5095
t-statistics	-	28.1405	-	25.7801
Conditional Variance Equation				
RESID(-1)^2	-	0.1388	-	0.1652
t-statistics	-	4.9616	-	5.6907
GARCH (-1)	-	0.7001	-	0.8799
t-statistics	-	20.2412	-	0.7348
Adjusted R^2	0.4365	0.6543	0.3773	0.6047
F statistic	487.4657	793.0061	351.2851	589.9910
Residual test				
ARCH Test F-Value	139.4875	24.6183	295.9094	32.3848
Obs*R^2	125.4249	24.1824	235.8111	31.5753
Durbin–Watson stat	1.1703	2.3659	1.0972	2.3453
Weekly				
Mean equation				
α	0.0221	0.0125	0.0293	0.0215
t-statistics	30.0061	9.1624	33.7829	18.1901
γ_1	0.2154	0.2171	0.2938	0.3026
t-statistics	5.3548	6.4064E-09	5.6638	6.6595

γ_2	0.5474	0.0368	5.2068	4.5201
t-statistics	1.9447	0.1412	9.6613	9.4457
AR(1)	-	0.3713	-	0.2021
t-statistics	-	7.9294	-	8.6701
Conditional Variance Equation				
RESID(-1)^2	-	0.0682	-	0.0617
t-statistics	-	1.0946	-	0.9621
GARCH (-1)	-	0.9295	-	0.4999
t-statistics	-	22.5647	-	3.2111
Adjusted R^2	0.4471	0.5551	0.8455	0.8821
F statistic	105.7501	108.3273	671.6902	609.1969
Residual test				
ARCH Test F-Value	1.5176	1.1982	3.2552	0.9255
Obs*R^2	1.5202	1.2014	3.2386	0.9295
Durbin–Watson stat	1.4502	2.1821	1.3656	1.8784
Monthly				
Mean equation				
α	0.0554	0.0572	0.0651	0.0425
t-statistics	19.7339	10.9417	17.9735	5.1552
γ_1	-0.2136	-0.2009	0.2446	0.2972
t-statistics	-2.2478	-2.0451	2.7358	3.4979
γ_2	3.2941	3.2349	0.0849	-0.1745
t-statistics	5.2462	5.0567	0.2161	-0.4665
AR(1)	-	-0.0372	-	0.2686
t-statistics	-	-0.4168	-	2.9368
Conditional Variance Equation				
RESID(-1)^2	-	-0.1156	-	-0.0383
t-statistics	-	-0.8637	-	-0.2797
GARCH (-1)	-	0.8921	-	0.3656
t-statistics	-	3.7043	-	0.5148
Adjusted R^2	0.5961	0.5892	0.4758	0.5541
F statistic	43.8138	28.2624	26.4155	23.7908
Residual test				
ARCH Test F-Value	0.7391	0.7461	0.1001	0.0782
Obs*R^2	0.7555	0.7628	0.1036	0.0811
Durbin–Watson stat	2.1403	2.0734	1.3807	2.1839

This table presents the regression results:$\mathrm{CSAD_t} = \alpha + \gamma_1|\mathrm{R_{m,t}}| + \gamma_2\mathrm{R_{m,t}^2} + \mathrm{e_t}$ for the BSE 500 and S&P 500 indices across daily, weekly, and monthly frequencies.

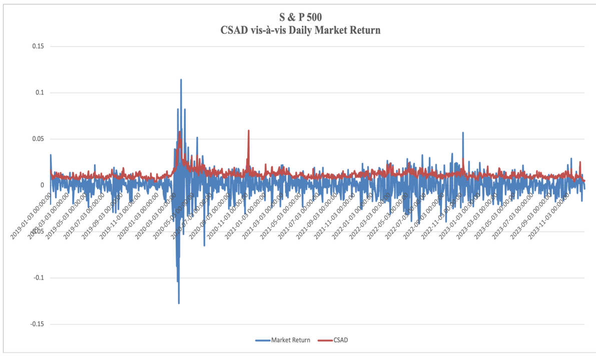

Fig. 1 CSAD vis-a`-vis Daily S&P Return

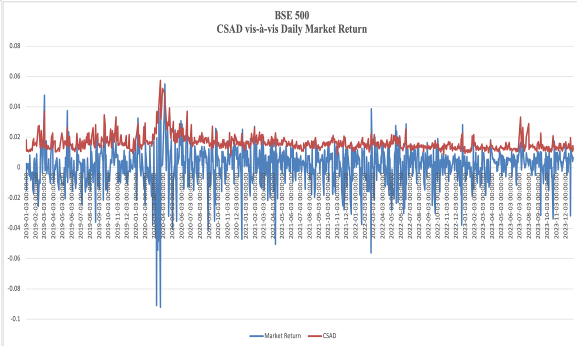

Fig. 2 CSAD vis-a`-vis Daily BSE Return

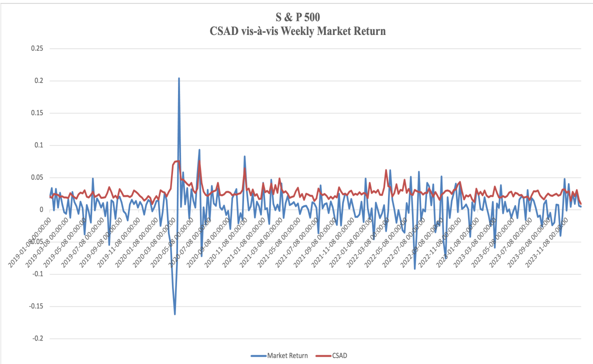

Fig. 3 CSAD vis-a`-vis Weekly S&P Return

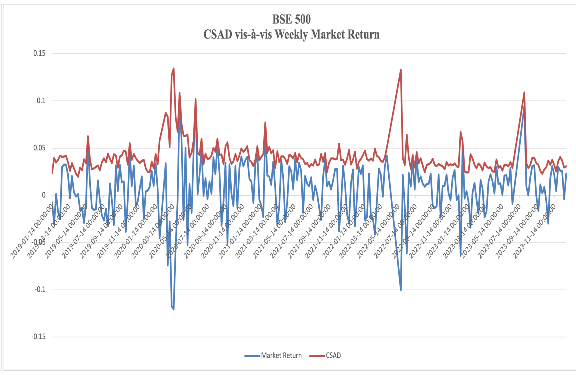

Fig. 4 CSAD vis-a`-vis Weekly BSE Return

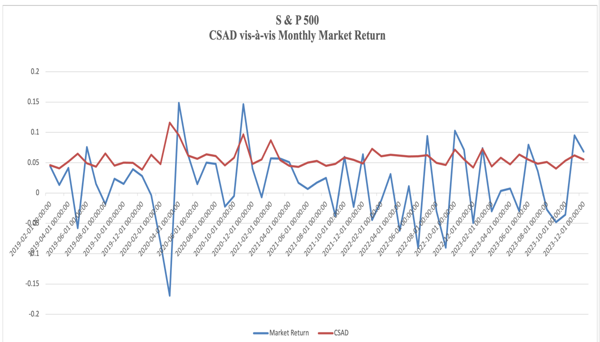

Fig. 5 CSAD vis-a`-vis Monthly S&P Return

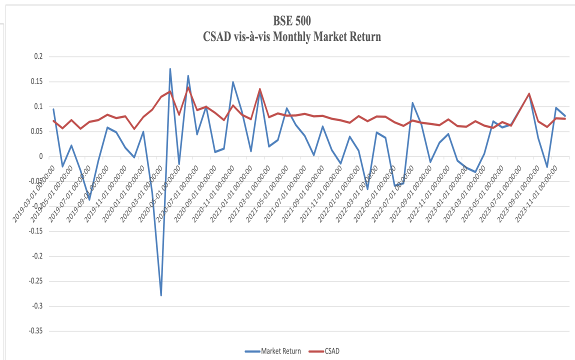

Fig. 6 CSAD vis-a`-vis Monthly BSE Return

Table 3 presents the CCK (2000) regression results of $\mathrm{CSAD_t}$ on the absolute and squared market returns for the BSE 500 and S&P 500 indices across daily, weekly, and monthly frequencies. The coefficients of the absolute market return γ_1 are generally positive and significant, indicating a positive linear relationship between market returns and cross-sectional dispersion, consistent with rational asset pricing. However, the monthly γ_1 for the S&P 500 is negative and significant, suggesting a slight convergence of individual stock returns during large monthly market movements, though herding is still not strongly evident. The coefficients of the squared market return γ_2 are mostly positive and significant across both markets, reinforcing the absence of herding behavior. Residual diagnostics reveal some autocorrelation and heteroskedasticity in weekly and monthly models, which are addressed by including AR(1) and GARCH(1,1) terms; these adjustments do not change the overall results. Overall, the findings indicate that investors in both markets generally make rational investment decisions rather than following the crowd, Figures 1–6 visually confirm these findings, showing a generally upward-sloping relationship between CSAD and market returns, consistent with rational trading behavior.

Table 4 Correlation between S&P and BSE

Monthly	
Correlation of CSAD S&P and BSE	0.4932
Correlation of Market Return S&P and BSE	0.5778
Correlation of Market Return Square S&P and BSE	0.7282
Weekly	
Correlation of CSAD S&P and BSE	0.5373
Correlation of Market Return S&P and BSE	0.4521
Correlation of Market Return Square S&P and BSE	0.4521
Daily	
Correlation of CSAD S&P and BSE	0.4786
Correlation of Market Return S&P and BSE	0.2562
Correlation of Market Return Square S&P and BSE	0.2562

The table reports the correlations between the S&P 500 and BSE 500 for CSAD, market returns, and squared market returns across daily, weekly, and monthly frequencies.

Table 4 shows that CSAD market returns and squared market returns between the S&P 500 and BSE 500 are moderately correlated with higher correlations at the monthly level and lower at daily and weekly frequencies indicating limited co-movement and that the two markets are largely influenced by different factors.

Table 5: UP Market Regression Result (CCK Model)

	S & P 500		BSE 500	
	Daily	Daily (With Newey-West)	Daily	Daily (With Newey-West)
Mean equation				
α	0.0089	0.0090	0.0134	0.0135

t-statistics	35.7906	24.869	50.0431	39.294
γ_1	0.3052	0.3053	0.1682	0.1682
t-statistics	10.7015	4.709	3.7676	2.961
γ_2	0.7506	0.7506	8.9306	8.9307
t-statistics	1.8095	1.058	6.9226	4.559
Adjusted R^2	0.4214	0.421	0.4358	0.436
F statistic	254.4841	229.6	279.0938	116.5
Residual test				
ARCH Test F-Value	27.8467	26.8497	107.0539	93.4228
Obs*R^2	26.8497	27.8468	93.4228	107.0539
Durbin–Watson stat	1.3632	1.363	1.0805	1.081
	Weekly	Weekly (With Newey-West)	Weekly	Weekly (With Newey-West)
Mean equation				
α	0.0211	0.0211	0.0288	0.0288
t-statistics	24.4228	22.017	25.6654	21.767
γ_1	0.2483	0.2484	0.2913	0.2913
t-statistics	5.3101	3.647	4.2541	3.285
γ_2	0.2538	0.2538	5.1312	5.1313
t-statistics	0.8471	0.765	6.4171	5.074
Adjusted R^2	0.4591	0.459	0.8046	0.805
F statistic	68.4575	32.14	318.2437	533.4
Residual test				
ARCH Test F-Value	0.4551	0.4595	0.0099	0.0101
Obs*R^2	0.4594	0.4550	0.0101	0.0100
Durbin–Watson stat	1.4184	1.418	1.5685	1.569
	Monthly	Monthly (With Newey-West)	Monthly	Monthly (With Newey-West)
Mean equation				
α	0.0502	0.0502	0.0805	0.0805
t-statistics	14.0725	18.667	17.2671	30.068
γ_1	-0.0497	-0.0497	-0.3007	-0.3007
t-statistics	-0.4059	-0.565	-2.1387	-3.608
γ_2	2.3916	2.3917	3.7173	3.7173
t-statistics	2.8096	4.739	4.4238	6.424
Adjusted R^2	0.5903	0.590	0.6293	0.629

F statistic	26.9394	276.4	34.1051	35.32
Residual test				
ARCH Test F-Value	0.3179	0.3335	0.4997	0.5198
Obs*R^2	0.3335	0.3179	0.5197	0.4998
Durbin–Watson stat	1.7331	1.733	1.5983	1.598

Table 5 reports the regression results of the CCK model for rising market conditions, $CSAD_t^{UP} = \alpha + \gamma_1^{UP}\left|R_{m,t}^{UP}\right| + \gamma_2^{UP} R^2{}_{m,t}^{UP} + \varepsilon_t$, $R_{m,t} > 0$ or the S&P 500 and BSE 500 across daily, weekly, and monthly frequencies.

In Table 5, the coefficients of the squared market return γ_2^{UP} are positive across all frequencies for both markets, indicating the absence of herding during up-market periods. Most coefficients of the absolute market return γ_1^{UP} are positive and significant, consistent with a linear relationship between market returns and return dispersion as predicted by rational asset pricing models, though the monthly γ_1^{UP} is negative for both indices, suggesting a slight convergence of returns during large monthly gains. Residual diagnostics show some heteroskedasticity and autocorrelation in weekly data, which is addressed using the Newey-West procedure; the adjusted models confirm the same results. Overall, these findings indicate that even in rising markets, investors in both the Indian and U.S. equity markets generally make rational investment decisions rather than following the crowd.

Table 6: Down Market Regression Results (CCK Model)

	S & P 500		BSE 500	
	Daily	Daily (With Newey-West)	Daily	Daily (With Newey-West)
Mean equation				
α	0.0097	0.0097	0.0137	0.0138
t-statistics	43.7998	25.888	49.7697	35.441
γ_1	0.2246	0.2247	0.16001	0.1600
t-statistics	9.5516	3.772	5.0156	2.915
γ_2	0.7369	0.7370	2.0837	2.0838
t-statistics	2.5863	1.509	4.0591	1.581
Adjusted R^2	0.4772	0.477	0.4231	0.423
F statistic	256.1662	85.45	160.5025	38.63
Residual test				
ARCH Test F-Value	356.7572	218.2498	13.4286	13.0849
Obs*R^2	218.4027	356.7573	13.0904	13.4287

Durbin–Watson stat	1.1139	1.114	1.2339	1.234
	Weekly	Weekly (With Newey-West)	Weekly	Weekly (With Newey-West)
Mean equation				
α	0.0238	0.0239	0.0297	0.0298
t-statistics	17.9297	15.071	21.1766	22.152
γ_1	0.1233	0.1234	0.3431	0.3432
t-statistics	1.5745	1.122	3.9663	3.775
γ_2	1.4018	1.4018	4.8046	4.8046
t-statistics	2.2459	2.161	5.8602	4.075
Adjusted R^2	0.4395	0.440	0.8793	0.879
F statistic	39.8143	101.4	328.8671	328.8
Residual test				
ARCH Test F-Value	0.4227	0.4296	23.7736	19.1425
Obs*R^2	0.4296	0.4228	19.1425	23.7736
Durbin–Watson stat	1.4595	1.460	0.9831	0.983
	Monthly	Monthly (With Newey-West)	Monthly	Monthly (With Newey-West)
Mean equation				
α	0.0631	0.0631	0.0628	0.0628
t-statistics	14.2851	26.299	14.4563	20.571
γ_1	-0.4656	-0.4657	0.1321	0.1320
t-statistics	-3.0761	-3.904	0.9742	1.261
γ_2	4.5417	4.5417	0.2663	0.2663
t-statistics	4.8913	6.669	0.5593	0.743
Adjusted R^2	0.6589	0.659	0.6234	0.623
F statistic	21.2861	173.2	14.2435	217.2
Residual test				
ARCH Test F-Value	1.3819	1.4239	0.4479	0.4960
Obs*R^2	1.4239	1.3820	0.4961	0.4479
Durbin–Watson stat	1.4255	1.426	1.9245	1.925

This table shows the coefficients representing the down-market conditions $CSAD_t^{DOWN} = \alpha + \gamma_1^{DOWN}\left|R_{m,t}^{DOWN}\right| + \gamma_2^{DOWN} R^{2}{}_{m,t}^{DOWN} + \varepsilon_t$, $R_{m,t} < 0$ of the S&P 500 and BSE 500 across daily, weekly, and monthly frequencies.

The same procedure is applied to declining market data using Eq. (6) in Table 6. Since the data is not continuous, the Newey–West procedure is used to correct for heteroskedasticity and autocorrelation in the daily, weekly, and monthly regressions. Overall, the results indicate that investors in both markets act rationally during down-market conditions, with no evidence of herding.

Table 7: Regression Results for CCK Model in Extreme Market Conditions

	S & P 500						BSE 500					
	DOWN			UP			DOWN			UP		
	1%	5%	10%	1%	5%	10%	1%	5%	10%	1%	5%	10%
Daily												
Mean Equation												
α	0.0044	0.0051	0.0051	0.0045	0.0051	0.0052	0.0072	0.0079	0.0077	0.0074	0.0079	0.0079
t-statistics	12.5316	14.5456	14.8642	12.7651	14.8302	15.5495	12.5091	14.4732	14.8849	15.8905	18.3319	19.1956
γ_1	0.0604	0.0948	0.0851	0.4581	0.2704	0.2285	-0.0998	0.0764	0.1287	0.5761	0.2334	0.2121
t-statistics	1.0548	3.7149	4.3354	6.7086	8.6688	9.3471	-1.0466	1.9903	4.5866	3.2821	3.8752	5.1516
γ_2	1.0707	0.8823	0.9966	-3.2894	-1.0432	-0.4177	3.7839	1.9044	1.2505	-5.7841	2.3681	3.1618
t-statistics	1.9391	3.1089	4.1826	-4.2314	-2.4043	-1.1352	3.2002	3.1966	2.6152	-1.4455	1.3739	2.4325
AR(1)	0.6167	0.5451	0.5411	0.6036	0.5358	0.5032	0.5288	0.4671	0.4669	0.5163	0.4707	0.4551
t-statistics	21.9429	18.9545	19.4289	21.4856	19.4724	18.2691	14.7892	13.5945	14.4331	17.7875	17.5541	17.6832
Conditional Variance Equation												
RESID(1)^2	0.1511	0.1216	0.1338	0.1662	0.1824	0.1834	0.2219	0.1974	0.2502	0.0389	0.0703	0.0841
t-statistics	3.6042	2.8885	3.1828	4.4381	4.8843	4.9138	4.7336	4.1877	5.3752	1.0429	1.8891	2.2624

GARCH (-1)	0.7999	0.8001	0.7999	0.6999	0.7001	0.6999	0.9299	0.6999	0.9301	0.7999	0.7999	0.7001
t-statistics	26.2482	22.5891	22.7794	20.7975	0.5586	16.1072	19.1665	13.2847	40.2399	27.2386	26.2472	21.3977
Adjusted R^2	0.6269	0.6571	0.6667	0.5387	0.5834	0.5985	0.4811	0.5445	0.5903	0.4679	0.5514	0.5887
F statistic	313.6172	357.3279	373.1149	271.5556	325.4913	346.4225	135.0940	173.9678	209.4937	211.8237	295.5978	344.1791
Residual test												
ARCH Test F-Value	12.9907	8.3438	10.1308	19.6965	23.8567	24.1461	22.4071	17.5368	28.8932	1.0877	3.5684	5.1186
Obs*R^2	12.7397	8.2501	9.9853	19.2075	23.1293	23.4005	21.4098	16.9307	27.2093	1.0891	3.5593	5.0974
Durbin-Watson stat	2.4451	2.4389	2.4249	2.4329	2.2862	2.3857	2.2596	1.5169	2.3411	2.1305	2.0999	2.0924
Weekly												
Mean Equation												
α	0.0153	0.0172	0.0164	0.0175	0.0172	0.0163	0.0296	0.0294	0.0317	0.0286	0.0302	0.0311
t-statistics	5.8744	7.4748	7.3581	10.7131	11.0809	10.7879	6.5446	11.8645	15.3232	10.0486	14.3644	16.6221
γ_1	0.1784	0.1828	0.1471	0.7409	0.3005	0.2424	0.5679	0.4728	0.2838	1.2995	0.2101	0.1745
t-statistics	2.9081	1.4573	1.7612	5.4274	5.0982	5.4922	3.5425	1.8774	2.2102	0.5601	1.2299	1.7941
γ_2	-	0.3451	0.6091	-2.3828	-0.1274	0.1894	-	2.2582	4.2718	-7.2271	4.3873	4.9953

t-statistics	-	0.3585	0.8601	-3.3155	-0.3523	0.6455	-	0.9521	3.3236	-0.3155	2.2452	4.0849
AR(1)	0.4396	0.3396	0.3494	0.3004	0.2890	0.3072	0.2844	0.2201	0.1335	0.2616	0.1849	0.1403
t-statistics	4.9375	4.2628	4.5477	5.0626	5.1058	5.6251	2.8436	4.0631	2.8928	3.8141	3.6177	3.0712
Conditional Variance Equation												
RESID(1)^2	-0.0485	-0.0677	-0.0555	-0.0076	0.0478	0.0868	0.0489	0.4822	0.2249	0.0476	-0.0191	0.0004
t-statistics	-0.4761	-0.6648	-0.5447	-0.0948	0.5934	1.0829	0.4572	5.1408	2.1545	0.5868	-0.2352	0.0053
GARCH(-1)	0.6046	0.8901	0.8901	0.8901	0.8691	0.8499	0.3918	1.011e-11	2.174e-14	0.0447	0.9941	0
t-statistics	4.0581	3.0802	4.7382	19.6198	16.6684	25.2441	2.8036	3.984e-11	6.275e-14	0.2073	26.8821	0
Adjusted R^2	0.3224	0.4796	0.5146	0.4575	0.5082	0.5387	0.2699	0.7671	0.8341	0.3467	0.6331	0.7131
F statistic	25.4533	31.1073	35.6345	45.4318	55.4265	62.5067	18.4316	98.7005	150.0626	28.0717	89.0034	127.7497
Residual test												
ARCH Test F-Value	0.2267	0.4421	0.2967	0.0089	0.3522	1.1727	0.2091	26.4283	4.6422	0.3444	0.0553	2.854E-05
Obs*R^2	0.2309	0.4491	0.3019	0.0091	0.3559	1.1789	0.2133	20.7366	4.5084	0.3481	0.0561	2.891E-07
Durbin-Watson stat	2.2708	2.2093	2.1101	1.9851	2.1493	2.1046	2.3036	2.0936	1.7141	2.1587	1.9152	1.9531
Monthly												

Mean Equation												
α	0.0547	0.0547	0.0549	0.0483	0.0486	0.0476	0.0551	0.0551	0.0534	0.0611	0.0748	0.0659
t-statistics	7.1009	7.0001	6.8628	5.3571	6.5207	6.8584	4.4143	4.4143	3.9645	4.8797	6.2115	7.2835
γ_1	0.3647	-0.2592	-0.4379	0.2819	0.1034	-0.1931	0.1695	0.1695	0.0051	0.2821	0.9251	0.5351
t-statistics	6.5592	-1.1203	-2.5275	3.2867	0.0158	-0.8412	4.0653	4.0653	0.0263	2.7945	0.5368	1.2839
γ_2	-	3.7025	4.7469	-	1.2319	3.2821	-	-	0.5899	-	-3.6412	-1.4751
t-statistics	-	2.4931	4.0444	-	0.0279	1.9327	-	-	0.7994	-	-0.3591	-0.5616
AR(1)	-0.0088	-0.0138	-0.0097	0.1307	0.1051	0.1085	0.1878	0.1878	0.2068	0.2521	0.0718	0.1529
t-statistics	-0.0691	-0.1065	-0.0744	0.8507	0.8271	0.9207	1.0745	1.0745	1.1108	1.7221	0.5018	1.4368
Conditional Variance Equation												
RESID(1)^2	-0.2186	-0.1702	-0.2282	-0.0273	-0.0718	-0.0491	0.0741	0.0741	0.0687	-0.0003	-0.0209	0.0724
t-statistics	-0.9411	-0.7301	-0.9837	-0.1567	-0.4131	-0.2826	0.2676	0.2676	0.2485	-0.0021	-0.1258	0.4359
GARCH(-1)	0	0	1.4632e-05	0.4503	0	0.9958	7.93e-06	7.930e-06	0.0231	0.82401	1.0	0.0411
t-statistics	0	0	4.8310e-05	2.6585	0	16.9131	3.72e-05	3.724e-05	1.3636	6.3311	15.4235	0.4091
Adjusted R^2	0.6221	0.6691	0.7106	0.1709	0.4547	0.5121	0.5192	0.5192	0.5688	0.1544	0.3436	0.5782

F statistic	22.0311	14.4774	13.9191	5.4083	10.7298	13.2405	12.0713	12.0713	7.5961	5.2341	7.6315	18.3653
Residual test												
ARCH Test F-Value	0.8857	0.5331	0.9676	0.0245	0.1707	0.0798	0.0716	0.0716	0.0617	4.7368E-06	0.0158	0.1901
Obs* R^2	0.9379	0.5753	1.0203	0.0261	0.1801	0.0845	0.0822	0.0822	0.0709	5.0000E−06	0.0167	0.1995
Durbin-Watson stat	1.3891	1.3853	1.4042	2.1482	1.9441	1.9773	2.5444	2.5444	2.5623	2.4981	2.1618	2.2386

This table presents the regression results of the CCK model for extreme market conditions, $CSAD_t^{DOWN} = \alpha + \gamma_1^{DOWN}\left|R_{m,t}^{DOWN}\right| * D_t^L + \gamma_2^{DOWN} R^2{}_{m,t}^{DOWN} * D_t^L + \varepsilon_t$, $R_{m,t} < 0$, $CSAD_t^{UP} = \alpha + \gamma_1^{UP}\left|R_{m,t}^{UP}\right| * D_t^U + \gamma_2^{UP} R^2{}_{m,t}^{UP} * D_t^U + \varepsilon_t$, $R_{m,t} > 0$ across daily, weekly, and monthly frequencies for the S&P 500 and BSE 500 at 1%, 5%, and 10% extreme thresholds.

Table 7 presents the coefficient of $\gamma_2^{UP} R^2{}_{m,t}^{UP}$ is negative and significant, indicating the presence of herding in extreme up-market conditions. Similarly, for the daily (1% and 5% level) and weekly (1% level) of S&P 500, $\gamma_2^{UP} R^2{}_{m,t}^{UP}$ is also negative and significant, suggesting herding during extreme upward movements. In contrast, for the BSE 500, the corresponding $\gamma_2^{UP} R^2{}_{m,t}^{UP}$ coefficients are not consistently negative or significant, indicating that herding is not observed in the Indian market even under extreme up-market conditions. Overall, while the US market shows some evidence of herding in extreme upward movements, the Indian market largely remains free from herding behavior.

Table 8: Regression Results for CCK Model in Normal Market Conditions

	S & P 500			BSE 500		
Daily						
	1%	5%	10%	1%	5%	10%
α	0.0035	0.0042	0.0045	0.0052	0.0073	0.0074
t-statistics	11.8148	13.1555	14.5291	13.5976	17.7345	18.6151
γ_1	-0.0732	-0.3465	-0.5472	-0.0522	-0.6971	-0.8817
t-statistics	-1.8756	-5.7463	-6.9417	-1.3007	-9.9139	-10.0822
γ_2	6.3364	21.5897	41.7022	8.7305	46.8283	69.6568

t-statistics	4.3346	6.0339	6.2612	5.7522	9.8776	8.5458
AR(1)	0.6896	0.7070	0.6995	0.6411	0.6334	0.6253
t-statistics	35.1113	36.3586	35.9661	30.6211	29.6333	29.2192
Conditional Variance Equation						
RESID(-1)^2	0.2417	0.2562	0.2492	0.2305	0.2087	0.2088
t-statistics	8.8198	9.3835	9.1109	8.0469	7.2495	7.2537
GARCH (-1)	0.7001	0.7001	0.7001	0.8800	0.9299	0.9299
t-statistics	15.1429	17.3559	0.4494	25.9486	70.7707	70.9686
Adjusted R^2	0.5498	0.5427	0.5473	0.4977	0.4822	0.4873
F-Statistics	512.0727	497.5833	506.7603	382.6041	359.6444	367.0535
Residual Test						
ARCH Test F-Value	77.7901	88.0511	83.0101	64.7536	52.5557	52.6169
Obs*R^2	73.3603	82.4011	77.9767	61.4167	50.3518	50.4079
Durbin Watson Stat.	2.4063	2.4418	2.4368	2.3523	2.3217	2.3191
Weekly						
α	0.0121	0.0142	0.0153	0.0251	0.0328	0.0325
t-statistics	6.4489	7.7252	8.8216	8.2135	10.6927	11.9133
γ_1	-0.0449	-0.4933	-0.7505	-0.4182	-1.8035	-2.1155
t-statistics	-0.4827	-3.3886	-4.4433	-2.5549	-7.3129	-8.1357
γ_2	2.6216	15.3034	25.5265	13.8091	50.4134	65.0376
t-statistics	1.6471	3.9237	4.1524	4.7701	7.5288	7.6629
AR(1)	0.5255	0.5358	0.5283	0.3815	0.4185	0.4215
t-statistics	9.6681	10.3985	10.3628	7.1499	8.0344	8.3134
Conditional Variance Equation						
RESID(-1)^2	0.1867	0.1926	0.2009	0.2144	0.2193	0.2205
t-statistics	3.0416	3.1411	3.2809	3.4156	3.4965	3.5173
GARCH (-1)	0.9301	0.9301	0.9195	0.5948	0.3475	0.5001
t-statistics	30.9608	29.7365	31.5308	2.8212	1.6396	2.5829
Adjusted R^2	0.3542	0.3651	0.3723	0.3581	0.3698	0.3891
F-Statistics	48.1813	50.4641	52.0091	46.3801	48.7312	52.8178
Residual Test						
ARCH Test F-Value	9.2515	9.8665	10.7643	11.6663	12.2261	12.3717
Obs*R^2	8.9986	9.5745	10.4134	11.2218	11.7344	11.8673
Durbin Watson Stat.	2.1851	2.1309	2.1331	2.1121	2.1655	2.1432
Monthly						
α	0.0633	0.0635	0.0634	0.0522	0.0619	0.0651
t-statistics	17.4502	16.2722	19.6404	5.7112	6.7141	6.2117
γ_1	-0.3688	-0.3543	-0.5621	-0.3667	-0.8131	-0.7559

t-statistics	-2.4325	-1.4091	-2.1351	-2.6171	-4.7749	-3.0755
γ_2	3.8549	3.7365	7.9592	4.5966	8.5165	7.7171
t-statistics	2.9781	1.2839	2.1412	4.7212	5.7777	2.8177
AR(1)	-0.0784	-0.0831	-0.0798	0.3452	0.3347	0.2971
t-statistics	-2.6873	-2.3746	-2.4292	3.6258	3.2886	2.4492
Conditional Variance Equation						
RESID(-1)^2	0.0598	-0.0027	0.0543	0.3939	-0.0114	-0.0767
t-statistics	0.4445	-0.0204	0.4027	3.1111	-0.0828	-0.5591
GARCH (-1)	0.8900	0.8895	0.8855	0.2999	0.7958	0.0767
t-statistics	10.4481	9.5073	9.2976	0.9295	7.1271	0.01394
Adjusted R^2	0.2867	0.1858	0.2219	0.5251	0.4414	0.1895
F-Statistics	8.6371	5.3371	6.4209	21.2694	15.4908	5.2864
Residual Test						
ARCH Test F-Value	0.1976	0.0004	0.1621	9.6785	0.0068	0.3126
Obs*R^2	0.2041	0.0004	0.1675	8.4928	0.0071	0.3225
Durbin Watson Stat.	1.8236	1.8623	1.9724	1.8556	2.1763	2.2155

Table 8 presents the CCK model results under normal market conditions $\mathrm{CSAD}_t^{\mathrm{Normal}} = \alpha + \gamma_1|\mathrm{R}_{\mathrm{m,t}}| \times N_t + \gamma_2\mathrm{R}_{\mathrm{m,t}}^2 \times N_t + \varepsilon_t$, $N_t = 1$, showing that for both the S&P 500 and BSE 500 across daily, weekly, and monthly frequencies.

Table 8 presents he coefficient $\gamma_2\mathrm{R}_{\mathrm{m,t}}^2 \times N_t$ is positive and statistically significant, while $\gamma_1|\mathrm{R}_{\mathrm{m,t}}| \times N_t$ is mostly negative. This indicates that the dispersion of individual stock returns increases with market movements, reflecting rational and independent decision-making rather than herding. In other words, during normal market conditions, neither the US nor the Indian market exhibits herding behavior. These results suggesting that herding in both markets is more context-dependent and occurs primarily during market stress rather than under normal conditions.

Table 9: Regression Results Using CCK Model in Different Time Frames

	S & P 500			BSE 500		
Daily						
	Pre-pandemic (Jan 1, 2019 – Dec 31, 2019)	Pandemic shock & high uncertainty (Jan 1, 2020 – Jun 30, 2021)	Post-Pandemic Recovery (Jul 1, 2021 – Dec 31, 2023)	Pre-pandemic (Jan 1, 2019 – Dec 31, 2019)	Pandemic shock & high uncertainty (Jan 1, 2020 – Jun 30, 2021)	Post-Pandemic Recovery (Jul 1, 2021 – Dec 31, 2023)

α	0.0051	0.0044	0.0057	0.0093	0.0059	0.0075
t-statistics	8.6617	9.1825	14.8662	11.0803	9.3293	16.2195
γ_1	0.1382	0.2202	0.0501	0.2227	0.1741	0.1629
t-statistics	2.4365	6.9895	1.6627	0.0034	4.8472	5.7661
γ_2	-1.2797	-0.1501	3.1514	6.1028	0.6281	0.5228
t-statistics	-0.5463	-0.4592	3.4419	2.7523	1.1719	0.6141
AR(1)	0.3889	0.5151	0.4152	0.2534	0.5678	0.3806
t-statistics	6.9831	15.4823	12.7331	5.0221	16.8191	11.8308
Conditional Variance Equation						
RESID(-1)^2	0.1322	0.1321	0.1984	-0.0089	0.1097	0.2386
t-statistics	2.0945	2.5719	5.0613	-0.1272	2.0529	6.0087
GARCH (-1)	0.5999	0.6999	0.8499	0.9701	0.8799	0.7999
t-statistics	8.4212	18.9914	136.0672	31.2493	14.6699	19.9807
Adjusted R^2	0.2335	0.7123	0.3683	0.5041	0.6723	0.4022
F-Statistics	26.2938	310.5338	122.8925	69.7861	239.0041	135.6128
Residual Test						
ARCH Test F-Value	4.3872	6.6146	25.6169	0.0161	4.2148	36.1048
Obs*R^2	4.3466	6.5343	24.6870	0.0163	4.1881	34.1629
Durbin Watson Stat.	2.0221	2.3431	2.2193	2.1578	2.4289	2.2116

Table 9 reports the results of the CCK model $\mathrm{CSAD_t} = \alpha + \gamma_1|R_{m,t}| + \gamma_2 R_{m,t}^2 + e_t$ applied to the S&P 500 and BSE 500 daily data across three sub-periods—pre-pandemic, pandemic shock and high uncertainty, and post-pandemic recovery—to examine herding under varying market conditions.

Herding behavior tends to be more pronounced during periods of high market uncertainty, to analyse for this we test the robustness of the results in Table 9. The γ_2 coefficient, capturing non-linear herding, is negative but not significant for the S&P 500 during pre-pandemic and pandemic periods, and positive post-pandemic, indicating no confirmed herding. For the BSE 500, γ_2 is positive throughout, showing no herding. Overall, investors in both markets did not exhibit significant herding, even during periods of high uncertainty.

Conclusion

We examine herding behavior in the Indian and U.S. stock markets. Herding, a well-recognized behavioral finance concept, refers to the tendency of investors to mimic the actions of others, whether rationally or irrationally. Such behavior can contribute to market inefficiencies and heightened volatility. Given the growing significance of India in the global financial landscape, understanding herding in its stock market is crucial for international investors who increasingly allocate capital to emerging markets. Indian markets are considered relatively less mature and more volatile compared to developed markets like the U.S., making the study of herding behavior essential to identify potential risks and inform effective investment strategies.

Based on the study of herding behavior in the Indian and U.S.A stock markets during the COVID-19 crisis, the study concludes that herding behavior is evident in the U.S. market, particularly during extreme upward market movements. In contrast, the Indian market shows no significant evidence of herding, even under periods of high uncertainty, indicating that investor behavior remains largely independent. These findings highlight that while developed markets like the U.S. may experience herding under bullish extremes, emerging markets like India benefit from more rational investment behavior, potentially due to the stabilizing influence of large institutional investors. Overall, the results represent the importance of market structure, investor composition, and regulatory frameworks in shaping herding tendencies across different markets. Future research could explore herding across investor types, examine other markets using high-frequency data, and assess the role of policies, regulations, and information in shaping herding behavior to improve market efficiency.

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