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The Impact of Herding Behavior in the Indian Stock Market during the 2025 US–China Trade Dispute

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Abstract

This study investigates herding behavior in the Indian stock market by analyzing high-frequency hourly data from the BSE 500 during the first quarter of 2025, during the period of rising global tension caused by the 2025 trade conflict between the US and China. The study utilized two distinct methodologies: the Cross-Sectional Standard Deviation (CSSD) model developed by Christie and Huang (1995) and the more robust Cross-Sectional Absolute Deviation (CSAD) model proposed by Chang et al. (2000). Our empirical findings were mixed but ultimately pointed to the presence of herding. The CSSD model indicated an absence of herding, showing that equity return dispersions tended to increase during periods of extreme price movements. However, the CSAD model uncovered strong evidence of herding, with a statistically significant negative coefficient. A detailed analysis revealed that this behavior was prevalent in both rising and falling markets. Specifically, herding was found during significant downward market movements, suggesting it is often a fear-driven response. This effect was notably absent during the most extreme crashes and was not statistically significant during extreme upward rallies. These results challenge the notion of a fully rational Indian market and highlight that external geopolitical events—like international conflicts , providing valuable insights for investors and regulators.

Key words- Herding behavior, Indian stock market, US- China trade disputes, CH model and CCK model

JEL Codes: G12, G14, C22, G15, D53

Introduction

From the beginning of stock trading, investors have tended to follow the crowd, especially when the market is uncertain. They buy and sell based on what others are doing, rather than on their own research. This collective behavior is called herding. This behavior can trigger sharp market movements that deviate from the true fundamentals of stocks. It has been cited as a key contributing factor to major financial crises, including the 1929 stock market crash, the dot-com bubble of the early 2000s, and the 2008 global financial crises, Shiller (2003). This is often seen when investors sell a stock at a low price simply because others are doing the same, or pay a high price for a popular stock.

A range of factors influence herding behavior. Investors may follow the crowd out of a belief that others possess better information, or they may be driven by psychological pressures like the fear of missing out or a desire to avoid standing alone in a wrong decision, Bikhchandani & Sharma (2000). It is also easier to go along with the crowd when there is significant uncertainty, limited time to make decisions, or a lack of reliable information, Avery and Zemsky (1998). Some investors may also engage in herding to protect their professional reputation or feel more confident by aligning with the majority, Scharfstein and Stein (2000). There are two main theories to defined herd behavior. From a rational perspective, investors deliberately follow others whom they assume

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possess superior information, while the irrational view argues they abandon their own analysis and follow the market purely due to psychological pressure, Rook (2006). Although herding might reduce individual decision-making stress, it often leads to **market inefficiencies, price bubbles,** or **overreactions**, as prices no longer reflect the true value of assets, Devenow and Welch (1996).

Early in 2025, tensions escalated between the United States and China two of the largest economies in the world and this drew global attention. Their trade dispute involved stricter tariffs on electronics, limitations on chip exports, and sanctions targeting major firms. These events caused widespread concern in global markets and significantly affected the Indian economy too. Even though India was not directly involved in the conflict, global uncertainties caused by the US–China trade tensions affected Indian investor sentiment and market behavior.

This study investigates herding behavior in the Indian stock market during a period of heightened global uncertainty, specifically the intensification of the US–China trade conflict. By analyzing investor actions during this key window, the research aims to understand whether external geopolitical events can trigger herding in a major emerging market like India. The remaining sections of the paper include detailed discussion of the US-China trade dispute, followed by the literature review, a section on methodology and data, an analysis of the results and discussion, and conclusion.

Us- China Trade Disputes 2025

In early 2025, following the re-inauguration of President Donald Trump, the US-China trade dispute intensified significantly. The conflict began on February 1, when President Trump increased tariffs on China by 10%. China responded three days later with tariffs of 15% on US goods like coal and natural gas, and 10% on crude oil and agricultural products. This back-and-forth continued, with Trump imposing an additional 10% tariff on March 3, bringing the cumulative tariff rate to 20%, and China retaliating with new tariffs of 15% and 10% on a range of US agricultural goods on March 4.

The disputes escalation reached a peak in April. On April 2, Trump raised tariffs by another 34%, resulting in a cumulative tariff rate of 54% on Chinese imports. China responded with a matching 34% tariff on all US goods on April 4. The tariffs eventually surged to an effective rate of 145% on Chinese goods by April 9, with China simultaneously imposing a retaliatory 84% tariff on US goods. By the end of April 2025, some tariffs reached as high as 245%, making it extremely expensive for companies to trade goods between the two countries.

Beyond tariffs, China also took non-tariff actions, including placing sanctions on major US firms and suspending exports of critical minerals essential for the auto and tech industries. The dispute created a highly volatile and unpredictable environment, significantly impacting global trade and creating the market stress also in India that this study will analyze.

Literature Review

Investor behavior has been studied for many years, with early observations noting the tendency of individuals to act collectively. One of the earliest ideas came from Keynes (1937) who introduced the concept of "animal spirits" to explain how emotions, rather than logical reasoning, often guide investment choices. This emotional influence can lead to irrational market behavior. Keynes's insight helped shape the foundation of modern behavioral finance, where herding is seen as a common and important psychological behavior among investors.

The concept of herding behavior in financial markets is grounded in early theories of informational cascades and social learning by Banerjee (1992) and Bikhchandani et al. (1992). These theories explain that under uncertainty individuals tend to follow others instead of relying on their own information. So, Herding behavior is a phenomenon in which investors disregard their own analysis and instead imitate the actions of others, defined by Bikhchandani and Sharma (2000).

A significant body of literature has been conducted on herding behavior in both developed and developing markets, but the findings have been varied. The theoretical studies explain herding as either a result of rational decision-making or psychological pressure, Scharfstein and Stein (1990). However, empirical studies have focused on testing its presence and effect on financial markets. One stream of research has found little to no evidence of herding. For example, Christie and Huang (1995), using a model that measures the dispersion of

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returns, found no evidence of herding in US markets. Similarly, Chang et al. (2000) did not find herding in the US, Hong Kong, or Japanese markets, even during periods of market stress. In another study, Tan et al. (2008) found no evidence of herding in the Chinese stock market. These studies generally suggest that investors in these markets are rational and independent, with their actions leading to an increase in return dispersion, which is the opposite of what herding predicts.

In contrast, a substantial number of studies have documented the presence of herding behavior across various markets. For instance, Wermers (1999) provided strong evidence of institutional herding in the US mutual fund industry. Nofsinger and Sias (1999) also found significant evidence that institutional investors herd in the US market. The phenomenon is not limited to developed markets. Chiang and Zheng (2010) found evidence of herding in a number of Asian stock markets, suggesting that herding is more prevalent in emerging markets. These findings collectively suggest that herding is a real and impactful force in many financial markets around the world.

Regarding the Indian stock market, research on herding is still developing. Early studies began to explore the topic, with Batra (2003) finding that foreign institutional investors in India showed a tendency to herd. Poshakwale and Mandal (2014) documented the existence of herding behavior in the Indian market, linking it to periods of high volatility. Similarly, Lao and Singh (2011) found herding in both Indian and Chinese stock markets, with stronger herding in India during sharp upmarket phases and periods of high volatility. Kumar et al. (2016) found no evidence of herding in the Indian stock market, even during extreme market phases. Ansari & Ansari (2021) found no herding in the Indian market, except during high-liquidity or high-sentiment periods. However, evidence remains mixed regarding whether herding behavior in India is persistent or episodic

Overtime, Researchers have examined the effects of herding behavior on price movements, market volatility, and efficiency. This behavior is evident during both stable periods and times of geopolitical or economic stress. Chiang and Zheng (2010) found that herding tends to increase during crises as investors respond in similar ways to global shocks. Similarly, Umar and Gubareva (2020) argued that geopolitical tensions impact volatility clustering and herding dynamics, especially in economies with high trade dependence. More recently, Oh and Kim (2024) examined the ongoing US–China trade dispute, which began around 2018, impacted investor sentiment and cross-border capital flows, possibly increasing herding in emerging markets like India. However, limited research has specifically examined at the effect of external trade conflicts, especially the US–China trade dispute, on herding behavior in Indian stock markets.

The present study seeks to provide insights into herding behavior in the Indian stock market, particularly within a unique and recent context. The US–China trade dispute of 2025 created a period of heightened global uncertainty and market stress, an ideal scenario for herding to emerge. By analyzing investor actions during this specific period, this paper aims to determine if this external geopolitical shock exacerbated herding behavior in a major emerging market like India.

Methodology and Data

Methodology

In the world of finance, investors are generally expected to make decisions based on available information and act rationally rather than being swayed by emotions. However in times of uncertainty or stress, people may tend to follow the crowd rather than making rational decisions independently. This behavior is called herding. This behavior can disrupt the flow of information in markets, causing assets to be mispriced and leading to unnecessary price fluctuations, Bikhchandani and Sharma (2000). To identify herding behavior, researchers have developed two key approaches:

1. Observing Specific Investor Groups: This means studying whether certain types of investors, such as mutual funds or foreign institutional investors, tend to make similar trades at the same time.
2. Analyzing Overall Market Trends: This involves looking at the overall behavior of all market participants to see if there is a widespread trend of buying or selling a specific asset at the same time.

The first approach to measuring herding behavior was developed by Lakonishok, Shleifer, and Vishny (1991). Their method determines whether a large number of fund managers are all buying or selling a specific stock at the

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same time. If this happens, it suggests they are following each other rather than making independent decisions. Their herding measure determines the statistical correlation of trading behavior among a group of market participants. It looks at the quarterly portfolio holdings of fund managers and identifies any coordinated trading behavior over time. The extent of herding in stock *i* during period *t* can be represented by:

$$H_{i,t} = \left|P_{i,t} - E\left[P_{i,t}\right]\right| - AF_{i,t} \qquad \text{.... (1)}$$

Where, $P_{i,t}$ is defined as the fraction of managers with a net buying position in stock *i* during period *t*.

$$P_{i,t} = \frac{B_{i,t}}{B_{i,t} + S_{i,t}}$$

$B_{i,t}$ = Number of institutional investors who increased their holdings of stock *i* (net buyers)
$S_{i,t}$ = Number of institutional investors who reduced their holdings (net sellers) of stock *i* during the same period.

$E\left[P_{i,t}\right]$ = Number of institutional investors who reduced their holdings (net sellers) of stock *i* during the same period.

$AF_{i,t}$ = is an **adjustment factor**, which accounts for expected random variation in buying behavior under the assumption of no herding, calculated as:

$$AF_{i,t} = \mathrm{E}\{\left|P_{i,t} - E\left[P_{i,t}\right]\right|\}$$

A higher $H_{i,t}$ implies stronger evidence of herding and under the null hypothesis of no herding, $H_{i,t}$ should be close to zero.

A significant limitation of the LSV model is that it requires detailed, firm-level trading data for specific investor groups. This kind of data is not easily accessible for the Indian market, particularly for domestic and Foreign Institutional Investors (FIIs), which has been a point of criticism by Wylie (2005). Therefore, the present study use the Christie and Huang (1995) (CH) and Chang, Cheng and Khorana (2000) (CCK) models as a more practical alternative. These models rely on market-wide data, which is readily available, to detect herding behavior. They focus on the collective actions of all market participants, rather than needing to track the trading of specific investor groups. The market-wide herding approach captures the behavior of the entire market, not just a select few groups.

The Christie and Huang (1995) (CH) model is based on two scenarios:

1. A Market Without Herdings- Individual stocks have varying reactions to market changes, which causes the returns of individual stocks to spread out as the overall market moves. The more significant the market movement, the greater the variation in returns among different stocks.

2. . A Market With Herding- Investors follow the crowd instead of conducting their own research, leading to a lack of spread in individual stock returns and a slower increase in return dispersion.

In order to measure the dispersion of returns, CH introduced the concept of Cross-Sectional Standard Deviation (CSSD).

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

Where N represents the total number of stocks included in the index sample, $R_{i,t}$ denotes the daily return of individual stock i on day t and $R_{m,t}$ indicates the daily market return corresponding to day t.

According to CH, herding behavior often happens when investors follow the crowd and make decisions based on what others are doing, especially during times of market uncertainty. This can be seen when there are big swings in the market that are not necessarily based on fundamental factors. Their research used the following equation to test this theory:

$$CSSD_t = \alpha + \beta_1 D_t^L + \beta_2 D_t^U + e_t \qquad ....(3)$$

Where CSSD is cross-sectional standard deviation, a measure of individual return dispersion, is used in this model to represent the impact of market stress on return dispersion, α coefficient measures the average dispersion of the sample for all periods except those specifically identified by the two dummy variables. D_t^L equal to 1 if, the market return ($R_{m,i}$) is in the lower tail of the return distribution on day t, and if not, then it is zero, D_t^U equal to 1 if, the market return ($R_{m,i}$) on day t is in the upper tail of the return distribution, otherwise it is zero, e_t represents the error term or residual for time period t, β_1 measures the cross-sectional dispersion responds to the magnitude of the market return i.e. the absolute value of market return) and β_2 captures any nonlinear effect, whether dispersion increases or decreases at an increasing or decreasing rate as market returns become more extreme i.e. through the squared market return. This study looks at extreme market movements by focusing on the top and bottom 1%, 2%, and 5% of hourly market returns, to identify significant changes in the market more easily.

The CH approach has several limitations. To begin with, it mainly identifies herding during periods of large market swings. Additionally, the threshold used to define an extreme market movement may not be consistent. It can vary from one investor to another and may also change as market conditions evolve over time. Herding behavior isn't limited to extreme market movements; it can happen across all market returns but becomes particularly strong during periods of market stress, Wermers (1999). Therefore, an alternative test known as the CSAD test developed by CCK has been introduced. CSAD captures return dispersion by computing the cross-sectional absolute deviation as:

$$CSAD_t = \frac{1}{N}\sum_{i=1}^{N}[\, R_{i,t} - R_{m,t}] \qquad ....(4)$$

CSAD can identify herding behavior under all market conditions, not only during extreme movements, using the formula below:

$$CSAD_t = \alpha + \gamma_1 |R_{m,t}| + \gamma_2 R_{m,t}^2 + e_t \qquad ….(5)$$

Where $CSAD_t$ cross-sectional absolute deviation of returns at time t, it measures how much individual stock returns differ from the market return on that day; α is the intercept. It captures the average level of dispersion when market returns are zero; γ_1 is the coefficient that shows how much return dispersion changes in proportion to the size of the market movement; $|R_{m,t}|$ is he absolute value of the market return at time t; γ_2 is negative, it means that when market returns get large, dispersion actually shrinks that suggesting herding; $R_{m,t}^2$ square of the market return. This allows the model to see if dispersion increases or decreases non-linearly and e_t error term.

The CCK model suggests that as market volatility increases the dispersion of individual stock returns also increases. This means that when the market is more volatile, individual stock returns tend to vary more widely. However, during times of large price changes where herding behavior occurs, the relationship between market return and return dispersion becomes nonlinear. To test this, they added the squared market return term $R_{m,t}^2$. A **negative** coefficient on this squared term shows herding and showing nonlinear relationship between return dispersion and market return during periods of extreme stress.

In herding literature Tan et al., (2008), it is recommended to analyze the impact of positive and negative market returns separately. This approach allows for a more detailed investigation into the level of herding behavior during both upward and downward market movements. To assess these asymmetric effects in herding behavior, the following equations are typically utilized:

$$CSAD_t^{UP} = \alpha + \gamma_1^{UP} |R_{m,t}^{UP}| + \gamma_2^{UP} R^2{}_{m,t}^{UP} + \varepsilon_t \,,\, R_{m,t} > 0 \qquad ….(6)$$

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$$CSAD_t^{DOWN} = \alpha + \gamma_1^{DOWN}\left|R_{m,t}^{DOWN}\right| + \gamma_2^{DOWN} R^2{}_{m,t}^{DOWN} + \varepsilon_t \text{ , } R_{m,t} < 0 \quad \text{....(7)}$$

Here, $\gamma_1^{UP}\left|R_{m,t}^{UP}\right|$ the linear relationship between market return and return dispersion during rising markets. If this coefficient is positive and significant, it supports rational asset pricing theory, and $\gamma_2^{UP} R^2{}_{m,t}^{UP}$ is the nonlinear term. If this coefficient is negative and statistically significant, it indicates herding behavior. $CSAD_t^{UP}$ *is the* Cross-Sectional Absolute Deviation (CSAD) of individual stock returns on day t when the market return is positive. Likewise, Equation (7) with the subscript DOWN is used to represent periods of market decline, where the corresponding CSAD captures the return dispersion during falling market conditions. Equation (6) examines herding during rising markets, while Equation (7) focuses on herding during falling markets. A significantly negative indicates herding behavior in bullish or bearish conditions, respectively.

Since herding behavior is more likely to occur during extreme market conditions due to psychological factors, the CCK model is applied to the hourly dataset using the following equations to examine herding during periods of extreme upward and downward market movements.

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

$$CSAD_t^{DOWN} = \alpha + \gamma_1^{DOWN}\left|R_{m,t}^{DOWN}\right| * D_t^L + \gamma_2^{DOWN} R^2{}_{m,t}^{DOWN} * D_t^L + \varepsilon_t \text{ , } R_{m,t} < 0 \quad \text{....(9)}$$

D_t^U is set to 1 if the market return on day *t* falls in the extreme upper tail of the return distribution, and 0 otherwise. Similarly, D_t^L equals 1 if the return falls in the extreme lower tail, and 0 otherwise. The thresholds for identifying these extreme tails are typically based on the top and bottom 1%, 5%, or 10% of the return distribution.

In order to ensure the reliability of the regression model, various tests are conducted to address issues such as stationarity, normality, autocorrelation, and heteroskedasticity of the error terms. The Augmented Dickey-Fuller (ADF) test is used to test for unit root, while residual tests like Jarque-Bera test, Durbin-Watson test, and ARCH LM test are employed to check for normality, autocorrelation, and heteroskedasticity, respectively. If these issues are detected, variable are changed and methods based on non-normality assumptions are applied. To address autocorrelation, lagged dependent variables are included in some equations. For heteroskedasticity, the GARCH(1,1) model is utilized, and the Newey and West consistent estimator is used for non-continuous data to adjust standard errors.

Data

This study examines herding behavior in the Indian stock market using hourly data from the BSE 500 index between January and April 2025, during the period of U.S.–China trade tensions. The BSE 500 is a broad and well-diversified index that covers about 93% of the market value on the Bombay Stock Exchange, making it a good representation of the Indian stock market. The BSE is selected for this study as it is one of the oldest and most prominent stock exchanges in India. The use of hourly data, collected from Yahoo Finance, helps in closely observing short-term herding patterns during this uncertain time.

Descriptive Statistics

Table 1 represents the descriptive statistics for the hourly measures of cross sectional standard deviation (CSSD_t), cross sectional absolute deviation(CSAD_t) and market returns ($\mathrm{R}_{m,t}$) for indian stock market. The data reveals rapid market swings and the varying spread of returns among stocks over short timeframes. The market's overall performance was a slight negative at -0.0137% with returns varying from a low of -5.7919% to a high of 2.1801%. The Indian stock market shows significant daily volatility, with equity returns fluctuating by a standard deviation of 0.5937%. In terms of dispersion, the mean values of CSSD and CSAD are 0.7407% and 0.5086% respectively. These figures highlight that individual stock performance can significantly diverge from the broader market's trend, even within short periods.

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Table 1: Descriptive statistics of the hourly data (January 2025 to April 2025)

Statistics	Hourly		
	CSSD	CSAD	$R_{m,t}$
Mean	0.7407	0.5086	-0.0137
Median	0.6334	0.4364	-0.0070
Maximum	4.1932	3.1258	2.1801
Minimum	0.1952	0.1312	-5.7919
SD	0.4255	0.3012	0.5937
skewness	2.1912	2.3786	-2.3163
Kurtosis	8.8234	11.2986	20.0520
Jarque-bera Test	1237.18	2131.14	7272.41
Probability	2.2472E-269	0	0
ADF Statistic	-3.9702	-4.3447	-6.8886
P-Value	0.001575	0.000371	1.37E-09
Conclusion	Stationary	Stationary	Stationary

Table 1 also specifies CSSD, CSAD, and market returns aren't shaped like a typical bell curve, as their skewness and kurtosis clearly show they're not normally distributed. Both CSSD and CSAD exhibit strong positive skewness 2.1912 and 2.3786 respectively, while market returns are negatively skewed -2.3163, indicating more significant declines than significant increases. The very high kurtosis numbers for CSSD 8.82, CSAD 11.30, and market return 20.05 imply leptokurtic distributions, meaning that extreme values occur more frequently than in a normal distribution.

Moreover, the statistically significant Jarque-Bera test results with extremely low p-values unequivocally confirm all three series are not normally distributed. This means any statistical models used, like OLS regression, must consider the crucial normal distribution assumption violation. We used the Augmented Dickey-Fuller (ADF) test on the raw series with an intercept to check for stationarity. The ADF test statistics for all three variables are highly significant, with p-values well below 0.01. These results lead to the rejection of the null hypothesis of a unit root, indicating that the series are stationary over the given time period.

The Empirical Results

To investigate herding behavior in the Indian stock market, we conducted a regression analysis using hourly data based on the CSSD (Cross-Sectional Standard Deviation) model proposed by Chang et al. (2000). In table 2 we introduced dummy variables to capture extreme market conditions at the 1%, 2%, and 5% capturing both extreme down (lower tail, D_t^l) and up (upper tail, D_t^u) movements. Across all three thresholds 1%, 2%, and 5%, the intercept α remains positive and statistically significant, with **t-statistics above 41**. This implies a strong baseline level of return dispersion (CSSD), even in normal market conditions.

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

$CSSD_t = \alpha + \beta_1 D_t^l + \beta_2 D_t^u + e_t$			
	Hourly		
	1%	2%	5%
α	0.00721	0.00701	0.00656
t-statistics	41.66513	42.38118	42.93575
β_1	0.00784	0.00836	0.00818
t-statistics	4.72164	7.48803	12.29755
β_2	0.010371	0.01003	0.00863
t-statistics	6.24126	8.98739	12.96520
Adjusted R^2	0.35067	0.19125	0.09505
F-Statistics	30.31	66.98	151.68
Residual Test			
ARCH Test F-Value	0.00016	0.0083	0.03276
Obs*R^2	0.00016	0.0083	0.03288
Durbin Watson Stat.	2.40702	2.40554	2.34928

The coefficients for the lower tail dummy variable (β_1) and the upper tail dummy variable (β_2) were both positive and statistically significant across all thresholds. This indicates that return dispersion actually increases during periods of extreme market returns, whether downward or upward contradicting the presence of herding behavior, which would be reflected by a reduction in dispersion as investors follow the market consensus. The findings suggest that investors act independently, especially in extreme market conditions, rather than displaying irrational herd-like behavior.

Additionally, the models showed strong statistical validity, with adjusted R^2 and F-statistics confirming overall significance. Residual diagnostics showed no signs of heteroskedasticity as per the ARCH test and minimal autocorrelation as Durbin-Watson values near 2. These results reinforce the conclusion that herding behavior is not evident in the Indian stock market when observed through high-frequency hourly data.

Since the Cross-Sectional Standard Deviation (CSSD) method has certain limitations in detecting herding behavior as noted by several researchers. This study also employs the Cross-Sectional Absolute Deviation (CCK) model. The use of the CCK framework allows for a more robust examination of herding effects and serves as a complementary test to validate the findings of the CH model. Table 3 presents the regression results from the CSAD model used to detect herding behavior in the market. The coefficient of the absolute market return $|R_{m,t}|$ is positive and statistically significant in both models, indicating that return dispersion tends to increase with market movement. More importantly, the coefficient of the squared market return $R^2_{m,t}$ is negative and highly significant.

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

$CSAD_t = \alpha + \gamma_1 \lvert R_{m,t} \rvert + \gamma_2 R^2_{m,t} + e_t$		
	Hourly	Hourly
Mean equation		
α	0.00318	0.00359
t-statistics	26.92283	18.2544
β_1	0.63717	0.62832
t-statistics	20.35191	20.0396
β_2	-7.17520	-7.14238
t-statistics	-7.77524	-7.7727
AR(1)	-	-0.07555
t-statistics	-	-2.6184
Conditional Variance Equation		
RESID(-1)^2	-	0.05194
t-statistics	-	1.22542
GARCH (-1)	-	0.48999
t-statistics	-	4.60799
Adjusted R^2	0.54585	0.55056
F statistic	336.33812	228.44058
Residual test		
ARCH Test F-Value	0.11597	1.50165
Obs*R^2	0.11636	1.50204
Durbin–Watson stat	2.19832	2.05549

However, It showing evidence of herding behavior as market returns become extreme and the dispersion of individual stock returns decreases. Model 2 further includes an AR(1) term, showing modest negative autocorrelation in CSAD. The GARCH(1,1) terms are also significant, confirming time-varying volatility in the data. The relatively high adjusted R^2 values and Durbin-Watson statistics close to 2 indicate a good model fit with minimal autocorrelation. Overall, the regression results provide strong support for the presence of herding behavior in the market during the sample period.

The Figure 1 presents the CSAD alongside hourly market returns. During periods of extreme positive or negative market returns, the CSAD line remains relatively stable instead of rising sharply. This lack of dispersion implies that most stock prices are moving in the same direction as the overall market, rather than behaving differently. Such behavior suggests that investors are following the crowd, which is a sign of herding.

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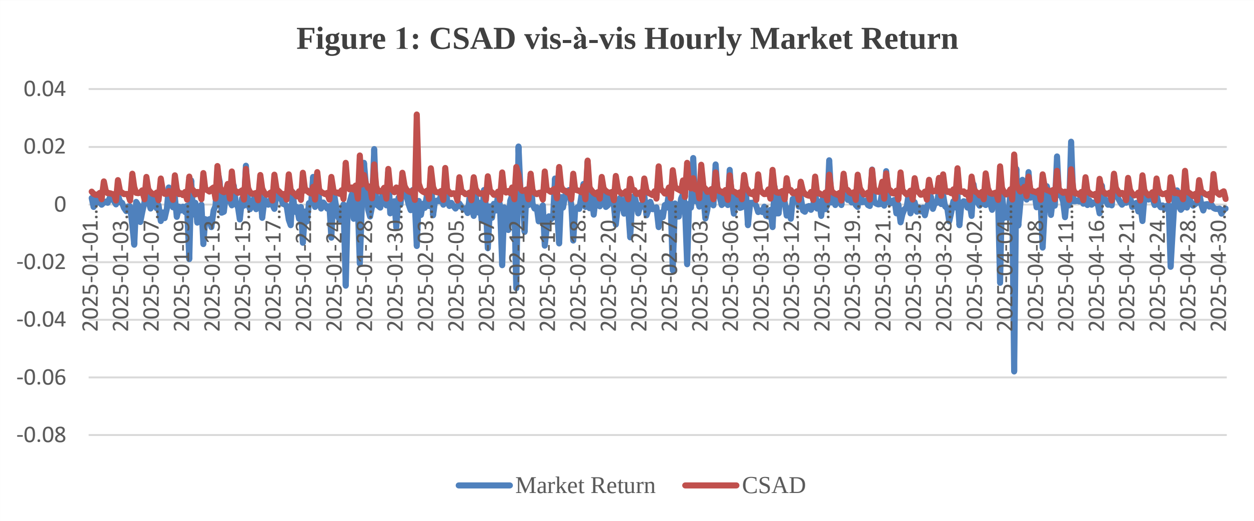

Table 4 shows the results of the regression model testing for herding behavior during rising market conditions in the Indian stock market, using hourly data. The regression equation estimates the Cross-Sectional Absolute Deviation (CSAD) of returns as a function of the absolute market return and the squared market return. The key finding is from the coefficient of the squared market return β_2. In this model, a negative and statistically significant β_2 coefficient is the primary indicator of herding. As shown in the table, the value for β_2 is -10.2522 with a t-statistic of -2.20. Because the t-statistic is greater than 2 in absolute value, this finding is statistically significant. This implies the presence of herding behavior in the Indian stock market during rising market conditions.

Table 4: UP Market Regression Result (CCK Model)

$CSAD_t^{UP} = \alpha + \gamma_1^{UP}\lvert R_{m,t}^{UP}\rvert + \gamma_2^{UP} R^2{}_{m,t}^{UP} + \varepsilon_t \, , R_{m,t} > 0$		
	Hourly	Hourly (With Newey-West)
Mean Equations		
α	0.0034	0.0034
t-statistics	18.83	21.15
β_1	0.6758	0.6758
t-statistics	9.02	8.597
β_2	-10.2522	-10.2523
t-statistics	-2.20	-2.12
Adjusted R^2	0.5598	0.560
F-Statistic	173.97	158.3
Residual test		
ARCH Test F-Value	0.0567	0.0571
Obs*R^2	0.0571	0.0567
Durbin–Watson stat	1.868	1.869

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The residual tests confirm the reliability of the regression model's findings. The ARCH test, which checks for heteroskedasticity (non-constant error variance), produced a low F-value, indicating the model's errors were consistent. Similarly, the Durbin-Watson statistic was close to 2, suggesting no significant autocorrelation (errors being correlated over time). To further validate the results, the Newey-West procedure was used as a robustness check. This method adjusts the standard errors to account for potential heteroskedasticity and autocorrelation, even if the tests didn't find them. The consistent results from the Newey-West procedure strengthen the evidence of herding. They confirm that the statistically significant negative coefficient is not tied to any one method. Since both approaches led to the same outcome, the evidence for herding becomes more reliable and convincing.

This analysis investigates herding in the Indian market during periods of downward price movement. Table 5 presents the results of the CCK model using hourly data. The primary finding comes from the coefficient of the squared market return, β_2. For herding to be present, this coefficient must be negative and statistically significant. As shown in the table, the value for β_2 is -6.8721 with a highly significant t-statistic of -5.93. This strong negative and significant coefficient provides clear evidence of herding behavior in the Indian market during a declining market. The results from the Newey-West adjusted model are consistent with the initial findings, strengthening the conclusion that herding is a statistically significant phenomenon in the down market.

Table 5: Down Market Regression Results (CCK Model)

$CSAD_t^{DOWN} = \alpha + \gamma_1^{DOWN}\lvert R_{m,t}^{DOWN}\rvert + \gamma_2^{DOWN} R^2{}_{m,t}^{DOWN} + \varepsilon_t \, , R_{m,t} < 0$		
	Hourly	Hourly (With Newey-West)
Mean Equation		
α	0.0029	0.0029
t-statistics	16.76	19.698
β_1	0.6309	0.6309
t-statistics	13.99	8.350
β_2	-6.8721	-6.8721
t-statistics	-5.93	-4.895
Adjusted R^2	0.5413	0.541
F-Statistic	169.13	160.7
Residual test		
ARCH Test F-Value	0.1462	0.1472
Obs*R^2	0.1472	0.1462
Durbin–Watson stat	2.0862	2.086

The analysis in Table 6 uses the CCK model to examine herding behavior during both extreme downward and upward market movements. The results for downward and upward market movements were analyzed separately at 1%, 5%, and 10% thresholds to capture varying levels of market stress. The analysis of the downward market reveals a nuanced picture of investor behavior. At the 5% and 10% thresholds, where markets experienced significant drops, the β_2 coefficient was found to be negative and statistically significant, providing strong evidence of herding. This suggests that investors tend to herd together during moderate to large market sell-offs. However, at the most extreme 1% market decline, the β_2 coefficient was negative but not statistically significant. This finding indicates that herding behavior might diminish during the most severe market crashes, possibly due to a shift towards more individualized and chaotic reactions.

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Table 6: Regression Results for CCK Model in Extreme Market Conditions

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

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

	DOWN			UP		
	1%	5%	10%	1%	5%	10%
Mean Equation						
α	0.00522	0.00458	0.00426	0.00533	0.00501	0.00471
t-statistics	15.85790	16.16203	16.06523	15.00697	15.85386	16.73865
β_1	0.39493	0.54594	0.54643	1.02051	0.68308	0.61236
t-statistics	2.44292	8.72539	11.22039	0.72815	3.43290	5.56053
β_2	-3.16705	-5.93897	-5.77173	-33.54055	-17.15631	-12.02362
t-statistics	-0.98619	-3.78278	-4.47428	-0.49150	-1.46202	-1.68471
AR(1)	-0.11293	-0.05389	-0.03708	-0.00041	0.012904	0.02034
t-statistics	-2.00216	-1.12616	-0.84080	-0.00707	0.24753	0.44164
Conditional Variance Equation						
RESID(-1)^2	-0.01009	-0.01938	-0.01368	-0.14720	-0.10149	-0.02265
t-statistics	-0.16945	-0.32559	-0.22981	-2.44100	-1.67326	-0.37170
GARCH (-1)	0.49000	0.49000	0.49000	0.49000	0.49000	0.49000
t-statistics	5.63495	4.97797	4.33454	7.20833	5.98025	0.70932
Adjusted R^2	0.10634	0.46203	0.36497	0.06193	0.26564	0.42674
F statistic	12.26477	82.30648	55.40940	6.96452	33.67784	68.24635
Residual test						
ARCH Test F-Value	0.02871	0.10601	0.05281	5.95848	2.79980	0.13816
Obs*R^2	0.0283	0.1067	0.0532	5.87470	2.79456	0.13912
Durbin–Watson stat	2.0437	2.18503	2.11785	2.00573	2.03737	2.06643

In contrast, the results for extreme upward market movements did not provide statistically significant evidence of herding. While the β_2 coefficients were consistently negative across all thresholds (1%, 5%, and 10%), none of these findings were statistically significant. This suggests that during periods of extreme market, investors do not conform to a collective behavior in the same way they do during a downturn. Therefore, even though the coefficients are negative, the results are not reliable enough to conclude that herding is definitely happening. The observed behavior in the up market could be a result of random fluctuations rather than a genuine herding phenomenon. This suggests that Indian investors may sometimes herd during extreme moves but it does not happen consistently.

Conclusion

This study investigates the presence and patterns of herding behavior in the Indian stock market in the context of the 2025 US–China trade dispute, a significant global economic event that could influence emerging markets like India. Herding is a psychological phenomenon where investors mimic one another, can lead to market inefficiencies and abnormal volatility. Our empirical findings, derived from a high-frequency hourly dataset and a rigorous two-model approach, our study provides valuable insights into investor behavior in one of the world's key emerging markets.

Initially, the analysis using the Chang and Huang (CH) model suggested the absence of herding. This model indicated that during extreme market movements, the cross-sectional standard deviation (CSSD) of returns tended to increase, which would support the idea of independent, rational investor behavior. However, this study also employed the more robust Chang, Cheng, and Khorana (CCK) model, which provided strong evidence that contradicts the initial finding. The CCK model's key coefficient was found to be negative and highly significant, a clear indicator that return dispersion decreases and herding is present in the market as a whole.

Specifically, the results indicate that fear-driven herding is more prevalent than greed-driven herding. While herding was a statistically significant factor during market sell-offs, it was not consistently found during extreme market rallies. These findings challenge the perception of the Indian market as fully rational and highlight the impact of major geopolitical events on investor psychology in emerging markets. The study contributes to behavioral finance by demonstrating that international events can shape investor psychology in emerging markets like India.

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