Major Project Report

on

BEHAVIOURAL BIAS IN INDIAN EQUITIES: A 20-YEAR STUDY OF HERDING PATTERNS ACROSS MARKET CONDITIONS

Submitted By

S Pranav Ranjan

23/DMBA/101

Submitted To

Dr. Chandan Sharma

(Assistant Professor)

DELHI SCHOOL OF MANAGEMENT

Delhi Technological University

Bawana Road, Delhi - 110042

CERTIFICATE

This is to certify that the Major Research Project titled "**Behavioural Bias in Indian Equities: A 20-Year Study of Herding Patterns Across Market Conditions**" is a Bonafide record of original work carried out by **Mr. S Pranav Ranjan**, Roll Number **23/DMBA/101**, in partial fulfilment of the requirements for the award of the degree of Master of Business Administration at Delhi School of Management, Delhi Technological University, Delhi.

This project has been completed under my supervision and guidance and is a genuine and original work to the best of my knowledge.

Dr. Chandan Sharma
(Assistant Professor)

Place: Delhi
Date:

DECLARATION

I, S Pranav Ranjan, hereby declare that the Major Research Project titled "**Behavioural Bias in Indian Equities: A 20-Year Study of Herding Patterns Across Market Conditions**" in partial fulfilment of the requirements for the award of the degree of Master of Business Administration (MBA), is a record of original work carried out by me under the supervision and guidance of **Dr. Chandan Sharma** at Delhi School of Management, Delhi Technological University.

I further declare that this work has not been submitted previously by me or any other individual for the award of any degree, diploma, or any other similar title in this or any other university or institution.

Place: Delhi
Date:

Signature of the Student
S Pranav Ranjan
MBA (Batch 2023–25)
Roll No: 23/DMBA/101

ACKNOWLEDGEMENT

I would like to express my sincere gratitude to all those who supported me throughout the course of this Major Research Project titled "**Behavioural Bias in Indian Equities: A 20-Year Study of Herding Patterns Across Market Conditions**"

First and foremost, I am deeply thankful to my faculty guide, **Dr. Chandan Sharma**, for his invaluable guidance, encouragement, and continuous support. I am also thankful to the subject faculty, Dr. Deepali Malhotra, for her insightful feedback and constructive suggestions were instrumental in shaping this research.

I would also like to thank the other esteemed faculty members of the Delhi School of Management, Delhi Technological University, for their constant academic support and inspiration.

I am equally grateful to my peers, friends, and family for their unwavering support, motivation, and understanding during the entire journey of this project.

This work would not have been possible without the contributions of each of the aforementioned individuals, and I express my deepest appreciation to all.

EXECUTIVE SUMMARY

This research investigates the incidence and dynamics of herding behavior — one of the main behavioral finance biases — in the Indian equity market for a complete 20-year period from 2005 to 2025. Herding bias is an inclination of investors to imitate the action of a large crowd of others rather than their personal judgment, particularly during uncertainty or big market moves. The research tests whether group behavior of such a kind can be empirically detected in the Indian stock market, how it varies across varying market conditions, and whether it varies across economic or external shocks-driven time periods.

The research employs secondary market data, and the focus is on daily stock prices of 39 frequently traded stocks of the Nifty 50 index and the Nifty 50 index. The sample for 20 years creates a strong foundation to examine hypotheses about behavior and detect structural changes in investor behavior over time.

To capture volatility in sentiment in the market and other macroeconomic events outside, the dataset has been split into five various time periods:

1. **Pre-Crisis Era (2005–2007):** A period of economic growth and upbeat investor sentiment before the global financial crisis.

2. **Global Financial Crisis (2008–2009):** A time of crisis with heightened volatility, uncertainty, and global market downturns.

3. **Post-Crisis Recovery (2010–2019):** Ten years of economic stabilization and market normalization.

4. **COVID-19 Era (2020–June 2021):** Defined by swift market dislocations, high investor anxiety, and quick recoveries attributed to the pandemic.

5. **Post-COVID Era (July 2021–2025):** A period of resurgence through economic reconstruction, change of investor sentiment, and emerging trends in equity participation.

In order to measure herding behavior, the research utilizes the Cross-Sectional Absolute Deviation (CSAD) approach used by *Chang, Cheng, and Khorana (2000)*. CSAD captures the average absolute deviation of individual stock returns from the market return for one day. Under conventional asset pricing theory, this deviation is assumed to rise linearly with the absolute market return because individual stock returns would stray farther in bad times in turbulent market conditions. However, when herding exists, investors will lean towards imitating the prevailing market consensus in trading behavior, and hence there will be a non-linear (concave) association between CSAD and market return. This implies that dispersion really falls when market activity is high — contrary to the assumption held by rational asset pricing — hence empirical evidence in favor of herding behavior.

The research fortifies its investigation by splitting each of the five time periods into bull and bear phases, so it is feasible to investigate the extent to which herding behavior is heightened in either a rising or declining market. Moreover, herding is investigated under conditions of extreme market states, i.e., on days of extreme positive returns and on days of abnormally large negative returns, to ascertain whether investor behavior is more collective when there is extreme stress or euphoria.

This research adds to the expanding literature of behavioral finance by employing a qualitative, in-depth quantitative method to measure non-rational investor behavior in a prominent emerging market. It offers useful insights for regulators, institutional investors, and fund managers to allow them to appreciate the subtleties of collective behavior and to identify possible inefficiencies in the Indian equity market. Moreover, by spanning two decades and addressing salient global and domestic events, the study provides a longitudinal analysis of how investor psychology changes and evolves as a function of changing market conditions. While the findings of this study will be presented in the subsequent sections, this paper provides a structured, evidence-based approach to the study of behavioral biases in financial markets, with particular reference to the Indian setting.

TABLE OF CONTENTS

CHAPTER 1
INTRODUCTION

Introduction to Finance and Behavioural Finance

Finance, both as a scholarly subject and as a professional field, has always been interested in how people and institutions allocate resources over time in a context of uncertainty. Conventionally, finance was based upon the twin foundations of rationality and effectiveness. Investors were assumed to be rational agents who methodically analyse all information they have access to, making utility-maximizing decisions. Similarly, financial markets were thought to be efficient—in the sense that prices at a point of time fully incorporate all current knowledge, a stance most famously encapsulated as the Efficient Market Hypothesis (EMH) of Fama (1970).

It was from such a classical perspective that a number of financial theories and models have emerged, such as the Capital Asset Pricing Model (Sharpe, 1964), the Arbitrage Pricing Theory (Ross, 1976), and the Modigliani-Miller theorem (Modigliani & Miller, 1958). Traditional finance was mostly concerned with building normative models that forecasted the behaviour of rational investors under ideal circumstances. Market equilibrium, risk and return, and the benefits of portfolio diversification were all of concern, always with the assumption that markets self-correct quickly and anomalies occur infrequently.

But as data piled up over the decades, researchers saw persistent departures from predictions from standard models. Markets were showing the formation of bubbles and their crashes, as well as anomalies such as reversal effects and momentum effects that rational models were having difficulty explaining. Investors, it became apparent, tended to behave inconsistently with the rational utility maximization assumption. This led to the development over time of a new paradigm called behavioural finance, aiming to add psychological insight to models of financial decision-making. Unlike conventional finance, which does not presume that investors are rational, behavioural finance investigates how cognitive constraints, emotional responses, and social pressures systematically shape financial conduct and market results. Its main concern is to explain real, observed investor conduct as opposed to prescribing optimal conduct. Behavioural finance attempts to determine how and why biases, heuristics, and irrationality afflict investment choices, with resultant market inefficiencies.

Therefore, finance today is at the intersection of its classical, rationalist antecedents and the new wealth of knowledge provided by the behavioural approaches. Knowledge of both camps is of the utmost importance for investors, researchers, and policymakers who want to understand more complex and dynamic financial markets.

Evolution and Importance of Behavioural Finance

The development of the science of behavioural finance was gradual rather than sudden as researchers and practitioners continued to encounter recurring patterns of data that could not be accounted for using classical finance theories. Fractures within the structure of rational finance first became evident around the 1970s and 1980s when pioneering research within the fields of economics and psychology began to reveal systematic patterns of error within people's judgment as well as decision-making.

The seminal work of Amos Tversky and Daniel Kahneman (1979) broke the risk-neutral rational agent assumption by illustrating that loss aversion and anomalies of decision making arise from the fact that humans value gains and losses asymmetrically. It was established through their work that people dread losses more than they value equivalent gains due to which they end up making irrational and inconsistent choices when they are under risk. Prospect Theory and other associated studies provided the platform for the development of Behavioural economics, which subsequently extended to Behavioural finance.

Simultaneously, there were empirical anomalies regarding asset pricing as well as market behaviour coming into the limelight. For example, the January effect, under which stock returns were excessively high in January, as well as the momentum effect, under which past winners kept performing, presented the Efficient Market Hypothesis with grave challenges (Jegadeesh & Titman, 1993). Robert Shiller's (1981) research on stock price excess volatility also challenged the premise that prices are always equal to fundamental values.

To account for these anomalies, Behavioural Finance started providing explanations from a psychological pattern perspective rather than a perfect rationality assumption. Overconfidence, regret aversion, and confirmation bias were some of the emotional influences that were incorporated into investor models. The significance of behavioural finance for contemporary financial research and practice cannot be overemphasized. It has increased the comprehension of market behaviour by demonstrating that prices are not always a reflection of rational anticipation of fundamentals. Rather, they may be consequences of collective emotions, cognitive biases (heuristics), and social processes.

Today, behavioural finance is applied to a broad range of practical uses:

- Portfolio management: Advising diversification approaches that take into consideration investor biases.
- Financial Planning: Adapting financial guidance according to clients' emotional requirements and behavioural patterns.
- Public Policy and Regulation: Designing mechanisms including 'nudges' for more effective financial decision making by citizens (Thaler & Sunstein, 2008).
- Risk Assessment: Merging behaviour patterns into frameworks to improve predictions of crashes and bubbles.

With a more globalized and uncertain financial climate, neglecting the behavioural factor would result in only partial as well as potentially risky analyses. Understanding the human factor within finance is key to creating more plausible models, superior financial products, as well as wiser regulation.

Hence, behavioural finance does not reject classical theories but extends them, providing a more complete, richer description of investor psyche as well as market patterns.

Overview of key Behavioral Biases

The systematic deviations from rationality of judgment as well as decision-making are known as behavioural biases within the context of behavioural finance. Cognitive-based biases determine the way people assess risk, gather information from the market, and reach conclusions. Overconfidence, anchoring, loss aversion, confirmation bias, as well as herding are some of the most popularly recognized biases. Each of these biases helps explain irrational investor attitudes as well as market inefficiency.

Overconfidence Bias

Overconfidence is the tendency for investors to overestimate their abilities, knowledge, and the precision of their forecasts. Overconfidence is responsible for excessive risk-taking, which results from the feeling of being capable of forecasting market trends more accurately than everybody else. Overconfidence may have the consequence of leading to overtrading, under-diversification, as well as sub-optimal investment choices (Barber & Odean, 2001). Overconfidence makes the investor overlook the role of chance that played a part in achieving successes while crediting failures to things beyond their control, instead of their choices.

Anchoring Bias

Anchoring happens when people overemphasize the first piece of information they receive (the "anchor") while making a decision. Investors may anchor expectations against previous stock prices or original estimates within financial markets, making no allowance for new, applicable information. For instance, an investor may keep a stock that lost a great deal of value because they base their perception on the stock's original high price, resisting adjustment that is called for (Tversky & Kahneman, 1974). Anchoring can impair decision-making by creating a bias towards irrelevant data.

Loss Aversion

Loss aversion, one of the core ideas of Prospect Theory, refers to the fact that people prefer avoiding loss over gaining equivalent gains. Psychologically, people feel losses more than they feel gains of the same absolute size. Loss aversion in financial markets can result in holding losing stocks, even though selling them would be rational. Investors instead cling to losing stocks hoping they will come back up, even though they end up reinforcing their losses (Kahneman & Tversky, 1979).

Confirmation Bias

Confirmation bias is the tendency to search for, interpret, and recall information that confirms existing beliefs while ignoring evidence to the contrary. Investors who are subject to confirmation bias might selectively concentrate only on confirming data that validates their investment hypothesis, without addressing data that implies they must reverse their positions. This bias can keep investors from making sound factual-based investment decisions and can facilitate suboptimal investment performance (Nickerson, 1998). Within the context of stock markets, confirmation bias can cause the continuation of stock market bubbles or extended trends.

Herding Bias

Herding refers to the behaviour where people imitate the actions of a majority, regardless of their independent judgment or analysis. This can result in irrational collective choices and dramatic market movements, i.e. speculation bubbles as well as panics. Investors herd when they do not have absolute confidence in their opinion and risk losing profits if they diverge from the crowd. Under conditions of market uncertainty, e.g. a financial breakdown or a surprise rally, the trend of herding is most visible, enhancing volatility as well as market inefficiency (Banerjee, 1992).

Each of these biases can occur independently, but they tend to interact with one another. Overconfidence, for example, can feed into herding behaviour because overconfident investors are more apt to herd because they are more convinced that they are doing what the majority are doing correctly. If market participants understand these biases, they are able to identify the psychological drivers involved, avoiding the pitfalls of irrational choices and market inefficiency.

Herding Behaviour and its Effects on Investor Perspectives

What is Herding Behaviour?

Herding behaviour is a situation where individuals follow others' behaviour, and not their own independent judgment or judgment. The social phenomenon of herding is well observed in the financial markets, where investors, as a group, adopt the same behaviour, for example, buying or selling a given stock, as influenced by the actions of others, and not based on their own analysis of the underlying fundamentals. The underlying premise of herding is that "if others are doing it, it must be the right thing to do." In financial markets, herding is most common in a state of uncertainty, crisis, or increased volatility of the markets. Investors, in a state of uncertainty, are following the crowd's actions and assuming that most people must know better or possess better information.

Herding behaviour can manifest itself in several different channels, such as mimicking institutional investors' action, following market direction even in the absence of sound fundamental backing, or reacting to sudden shifts in market sentiment. The behaviour is not restricted to retail investors; in fact, even professional investors, such as fund managers and institutional traders, are susceptible to herding behaviour, especially under circumstances of career risk or peer pressure in their decision (Bikhchandani, Hirshleifer, & Welch, 1992).

Psychological Explanations for Herding

The tendency to go along is motivated by a number of psychological issues. These are:

- Fear of Missing Out (FOMO): Refers to the fear that investors have of missing an opportunity if they fail to imitate others' behaviours. This fear will always lead to irrational decision-making whereby individuals rush to invest based on others' behaviours without properly analysing the risks involved (Pratt, 2019).

- Social Proof: Individuals tend to look to others for advice, especially when they are uncertain or in a state of ambiguity. Social influence can result in herding, where individuals use the crowd's collective knowledge, believing that others possess superior or more valid information (Cialdini, 2009).

- Cognitive Dissonance: When people experience a sense of internal conflict or doubt about the decisions they make, they look for external validation. Herding behaviour provides a sense of security because it minimizes the pain of making decisions that go against the majority opinions in the market (Festinger, 1957).

- Risk Aversion: Investors use quantitative information under market uncertainty or where ambiguity exists. Herding can be a risk-defensive mechanism to offset the expected risk of being incorrect, as imitating the crowd gives one a feeling of safety (Devenow & Welch, 1996).

The Impact of Herd Behaviour on Investor Sentiment

Herding behaviour can affect the market attitudes that investors entertain and even their own investment approaches. Among the major impacts are:

- Overdependence on Group Decisions: When the majority is being followed by the investors, it is usually based on the presumption that the majority choice is correct, and therefore, there is a false sense of security. This overdependence can result in the neglect of personal analysis or the dismissal of possible risks. This can further intensify market trends, which can result in price rises or falls (Shiller, 2000).

- Conformity and Loss of Independent Judgment: Herding can lead to loss of independent thinking and critical analysis. Investors may be inclined to follow the group, especially in environments where social influence is high. This may result in suboptimal decision making and the amplification of irrational behaviour in the market (Hirshleifer, 2001).

- Short-Term Orientation: Herding tends to favour short-term gains over long-term value. Investors are able to rapidly purchase or sell a security in response to prevailing market trends, driven by the behaviour of others, without considering long-term the wisdom of their behaviour. This can create market inefficiencies and volatility, as short-run trends overwhelm the underlying value of assets (Barberis, Shleifer, & Wurgler, 2005).

- Distortion of Market Prices: perhaps the most important impact of herding behaviour is the distortion of market prices. As many investors emulating one another, they push asset prices out of line with their actual values. This can result in the creation of bubbles, where the prices of equities or other assets become artificially inflated through bulk purchases, or crashes, where sudden dispositions lead to a sudden plunge in prices. Cases such as the 2008 Global Financial Crisis and the market instability during the COVID-19 pandemic demonstrate how herding disrupts market pricing mechanisms and enhances systemic risk.

Herding Behaviour in the Context of Indian Financial Markets

In India's equity market, herding behaviour has been increasingly evident, especially with the growing retail investor participation and the widespread application of social media sites to post market-related content. Indian equities' economic liberalization, coupled with growing retail investor participation and enhanced access to various investment instruments, has facilitated herding behaviour in the market to rise at a fast rate. India's leading 50 listed companies' representative index, the Nifty 50, frequently experiences surges in herding behaviour, particularly during periods of economic optimism or turmoil.

The rapid adoption of online trading apps and mobile websites has allowed retail investors to move with ease as markets move, frequently mimicking others on online forums or on social media. Events like the COVID-19 pandemic, for instance, have seen massive market movements led by retail investors, with social media influencers and online forums driving sentiment among investors. The result saw speculative trading increases, with investors herding into rapidly rising shares, frequently regardless of the fundamental factors.

In the context of India, this herding can be boosted by the existence of information asymmetry, i.e., retail investors might not have access to information as equally as institutional investors and hence rely more on others' actions. Additionally, the sentiment-driven nature of India's equity market, which is generally fuelled by domestic news, political happenings, and macroeconomic factors, can fuel herding during uncertainty or market volatility.

Implications of Indian Financial Markets' Collective Behaviour

The impact of herding behaviour in Indian financial markets is diverse and mixed. While it can spread information quickly and increase market liquidity, it is usually accompanied by extreme market distortions.

- Volatility: Herding can result in abrupt price changes in assets, which further enhance volatility. Both institutional and retail investors feel this volatility, and the market becomes a one where prices do not necessarily represent the true value of equities.

- Speculative Bubbles: Herding is usually the reason for the creation of speculative bubbles when asset prices balloon far above their intrinsic value because of general optimism. When the herd turns around, these bubbles burst, and there are steep falls in prices and heavy financial losses.

- Market Inefficiencies: The inclination of investors to overlook fundamental analysis in favour of herd behaviour can lead to market inefficiencies. These inefficiencies contradict the theoretical foundations of the efficient market hypothesis (EMH) and lead to asset mispricing, which can be harmful to investors who make decisions on the basis of fundamental analysis.

Theoretical Foundations of Herding Behaviour in Financial Markets

Theories of Herding Behaviour

Herding behaviour within financial markets can be explained through a number of important theoretical frameworks that attempt to explain why people, or groups of people, may follow collective approaches over solely relying on their own personal judgment. These theories shed light on the mechanisms of herding behaviour and its impacts on market structure.

- <u>Theory of Information Cascades</u>

  The information cascade phenomenon is applied to a scenario where people decide what to do based on what other people are doing, and not from private information. It can happen where one sees what other people are doing and concludes that they have superior knowledge. Therefore, they end up doing the same thing even if they possess personal information that advises against it.

  The model of information cascades was initially formulated by Bikhchandani, Hirshleifer, and Welch (1992). They explained that if people are unsure of a decision, they might opt to overlook their private information and instead observe the actions of other people, assuming that collective action is a more valuable or superior source of information. This can result in a market setting where people overlook their personal research and only follow the actions of other people, even if it creates market inefficiencies or a bubble.

  Implication for Financial Markets: Information cascades have the potential to cause severe mispricing of assets because people tend to act under the assumption that other people have superior or superior information when, as a matter of fact, they do not. This can create speculative bubbles as well as crashes when market decisions deviate from true values.

- <u>Role of Social Learning</u>

  Social learning focuses on the fact that people acquire knowledge from the actions of other people, particularly when they are uncertain or do not have information. It can result from people imitating the actions of market participants with more experience or success, for instance, institutional investors or renowned analysts.

  This form of learning can be especially robust where knowledge is sparse or hard to decipher. Here, imitating the crowd acts as a shortcut for making choices that are safer than bucking the trend. Herding behaviour tends to reinforce social learning, as people are motivated to fall back on collective understanding instead of performing independent analysis.

Implication to Financial Markets: Investors will sometimes imitate the actions of their counterparts even when it is not optimal for themselves, particularly if they believe that their knowledge is insufficient. This creates the amplification of positive as well as negative trends within the market.

- <u>Prospect Theory and Loss Aversion</u>

  Prospect Theory, which was put forward by Kahneman and Tversky (1979), is another influential model for describing herding behaviour. This theory posits that people feel a greater amount of pain resulting from losses compared to pleasure derived from similar gains (loss aversion). Financial markets can exhibit a resultant herd behaviour as a consequence of this, as a result of which investors respond to prospective loss by imitating the crowd for fear of adverse results.

  It is possible for investors to herd as a method of avoiding making the wrong decision because they are apt to follow what everyone else thinks instead of risking divergence from the majority. It can result in market participants resorting to herd-like behaviour under conditions of uncertainty, even if it is irrational.

  Implication for Financial Markets: Loss aversion as well as fear of error can create herding, particularly under stress market conditions or market declines. Investors can shy away from assuming a contrarian stance, even if such a stance is more rational under given information.

- <u>Behavioural Finance and Market Inefficiencies</u>

  Behavioural finance is a discipline that synthesizes economics with psychology as they attempt to account for market anomalies, such as herding behaviour. Contrary to conventional finance, where markets are held to be efficient under rational agents, it is suggested by the former that investor decision-making is determined by psychological elements, including biases and emotions.

  Herding is generally fuelled by emotional contagion, with the crowd's emotional condition affecting individual choices. For instance, if there is a sense of excessive optimism or fear among the investors, these sentiments can be contagious and prompt other people to follow the same stance even if there is no new information. This can lead to overreactions to market occurrences, such as the formation of asset crashes or bubbles, as well as market inefficiencies.

Implication for Financial Markets: Behavioural finance implies that markets are never efficient because emotions and biases can cause irrational collective behaviour. Psychological biases can force prices away from their fundamentals, creating volatility as well as mispricing of assets.

Market Microstructure and Herding

The theory of market microstructure addresses the mechanics surrounding the buying and selling of securities. It examines how market design and the information that participants have affect behaviour in the market. It can explain how there may be herding in financial markets.

- Information Asymmetry and Herding

  Information asymmetry refers to a situation where market participants have unequal levels of access to information. Institutional investors have superior access to information compared to retail investors, a fact that can lead to a biased decision-making process.

  Individual market participants without access to the same resources, information, or level of expertise as institutional investors are more inclined to imitate the moves of more substantial, more seasoned market participants. This creates the phenomenon of herding because people are copying the investment style of those who are viewed as having superior information, even if they are doing so without thorough research.

  Implication for Financial Markets: Information asymmetry can worsen herding behaviour because less-informed investors may follow the actions of more-informed agents, which can even further bias market prices.

- Market Liquidity and Herding

  Market liquidity is the degree to which assets can be bought or sold without impacting their prices. It is easier to trade huge volumes of assets without displacing the market when there is market liquidity, while even tiny trades can move markets a long way when there is illiquidity.

  Herding can be particularly troublesome in illiquid markets because the crowd's mass buying or selling can disconnect prices from the asset's underlying value. If a crowd of investors all rush to follow the same market trend, they can create volatility by causing the price to move to extremes.

  Implication in Financial Markets: Low liquidity can reinforce herding behaviour because crowd-sized trades are able to shift market prices powerfully. This can result in volatile price fluctuations.

Empirical Evidence of Herding in Global and Indian Markets

<u>Global Research into Herding</u>

Much empirical work has confirmed the existence of herding in many financial markets across the globe. These works employ a range of methodologies and datasets to investigate the circumstances, timing, and motive for the existence of herding in different contexts.

<u>Advanced Economies</u>

Studies focused on developed markets, such as those in the United States, Europe, and Japan, have provided inconclusive findings related to herding behavior, often driven by existing market conditions.

Christie and Huang (1995) authored one of the first studies of this topic. They suggested the Cross-Sectional Standard Deviation (CSSD) method for detecting herding behavior during times of market stress in the United States. They found little evidence of herding, other than at the extremes of market movements.

Based on the previous research, Chang, Cheng, and Khorana (2000) utilized the Cross-Sectional Absolute Deviation (CSAD) approach. The results were stronger evidence for a non-linear association between dispersion and market returns, which implies that herding is more intense when market returns are high.

Equally, research conducted in Europe revealed that herding behavior grows in times of crisis, as the European sovereign debt crisis would indicate.

In Japan, research emphasized herding by institutional investors, particularly in times of uncertainty.

Key Findings

- Herding behavior is likely to peak during times of market stress.
- Institutional herding, especially by mutual funds and pension funds, has been extensively documented. Sophisticated markets have both rational (information-based) and irrational (emotion-based) herding.

Emerging Markets

The herding effect is more pronounced in emerging markets compared to developed markets.

Demirer and Kutan (2006) researched herding in emerging stock markets such as Korea and Turkey, and they found high herding, particularly when markets were declining.

Studies targeting the Latin American and Asian markets indicate that informational inefficiencies, decreased transparency, and investor cognitive biases typical of investors firmly encourage such herding in the two markets.

The presence of market inefficiencies and the dominance of retail investors typically increase the degree of herding behavior seen in emerging markets.

Principal Findings:

- Information asymmetry is higher in emerging markets, and it motivates crowd-following behavior.
- In emerging markets, herding tends to be more persistent and stronger than in developed markets.

Herding Behavior in Indian Equity Markets

In recent years, research has increasingly turned its focus toward understanding herding behavior within India’s equity markets, especially given the country's unique market structure and characteristics.

Early Evidence

Panda and Nanda (2017) applied the CSAD methodology to stocks listed on the Nifty 50 and discovered significant herding behavior during both rising and falling markets.

Lakshman, Basu, and Vaidyanathan (2013) found evidence of asymmetric herding in India, noting that it tends to be more pronounced during market downturns.

Sinha (2010), using a different analytical approach by studying correlation structures among stocks, provided further evidence of collective behavior in the Indian equity market, especially during periods of heightened volatility.

Recent Studies

Recent studies point to the existence of sector-specific herding, which indicates that investors are likely to exhibit more intense herding behavior in some sectors, for example, technology, banking, and infrastructure.

Chakrabarti et al. (2020) pointed out the significant effect that Foreign Institutional Investors (FIIs) play on herding in India. The investment decision of such investors has a tendency to induce overreaction in the market.

Research carried out after 2016, particularly after sweeping policy changes like demonetization and the rollout of the Goods and Services Tax (GST), suggests that increased policy uncertainty has abetted the herding behavior of retail and institutional investors alike.

Major Observations:

- Herding behavior is supported in times of market decline and policy uncertainty
- Individual investors are responsible for contributing to herding to a large extent, primarily because they have relatively lower access to credible information.
- The actions of international investors can induce or amplify herding behavior in the local markets.

Brief Methodology

<u>Research Objective</u>

The primary objective of the study is to analyze the incidence and direction of Indian equity investor herding behavior over 20 years from 2005 to 2025 based on Nifty 50 stocks.

We intend to:

- Recognize that there is widespread herding.
- Explain how herding behavior is different in different market conditions (upswings, downswings, high volatility).
- Investigate if and how far external influences (e.g., policy, global crises) impact herding behavior.

<u>Data Collection</u>

- Data Source: Secondary data for this study were sourced from **ProwessIQ**, a financial database updated regularly by the Centre for Monitoring Indian Economy (CMIE).

- Sample Selection: 39 that consistently represented a subset of the Nifty 50 for the majority of the research horizon were selected.
- End of the day closing share prices, and Nifty 50 index prices were utilized daily.

- Time Frame: From January 1, 2005, to March 31, 2025.

Computed Variables:

- The daily returns are calculated using logarithmic returns.
- Market Return: Individual stock return average or Nifty 50 index return.
- Cross-Sectional Absolute Deviation (CSAD): The main metric for herding detection.

Data Cleaning and Processing

Tools Used:

1. Microsoft Excel: Used in the calculation of daily returns and CSAD values.
2. IBM SPSS: Used in regression analysis.

Steps Taken:

- Missing values (trading holidays, say) were handled with care — missing price-data intervals were deleted or filled in on a consistency basis.
- Outliers were detected but not removed intentionally, so that action is not skewed in the presence of unusual market activity (where herding occurs).
- Variables such as Market Return, |Market Return|, and (Market Return) ^{2} were defined to be used in regression analysis.

Model Employed in Analysis

The CSAD model of Chang, Cheng, and Khorana (2000) was employed to identify herding behavior.

Why CSAD?

In contrast to standard deviation (used in previous work such as Christie and Huang), CSAD is better suited to specify non-linear relationships between market movement and dispersions in returns.

Sub-Period Analysis

To grasp better how herding behavior evolved under different market circumstances, the whole period of 20 years was divided into five sub-periods:

- Pre-Crisis Period (2005–2007): A period of robust economic growth and upbeat market sentiment before the onset of the Global Financial Crisis.
- Global Financial Crisis (2008-2009): Crisis period marked by unprecedented market turbulence, panic, and increased uncertainty.
- Post-Crisis Recovery (2010–2019): ten years of consistent market recovery, economic recovery, and prolonged investor participation.
- COVID-19 Phase (2020–June 2021): Marked by extreme pandemic-induced dislocation, panic, sudden market dips, and corresponding quick bounce backs.
- Post-COVID Recovery (July 2021–2025): A period of economic rebalancing, digitalization, and shifting retail investor sentiment.

Each sub-period was subjected to individual regression tests to see whether herding behavior was more pronounced in periods of high market volatility or sudden economic change. This segmentation allowed the study to track the dynamic evolution of investor psychology over time and shifting macroeconomic conditions.

Importance and Relevance of the Study

1. Understanding Investor Behavior

   This research de-mystifies the psychological forces behind investor choices, particularly during uncertainty. By analyzing herding behavior, it sheds light on how sentiments like fear and greed shape the behavior of the market and drive investor choices.

2. Implications for Market Efficiency

   Herding is most likely to create market inefficiencies that result in mispricing and volatility. An understanding of such behaviors enables market participants to expect and mitigate the negative impact of irrational choice and thus more stable markets.

3. Policy and Regulatory Significance

   To policy-makers, the study is helpful in terms of knowing how destabilization of the market can be caused by herding behavior on the part of investors. Understanding how herding behavior operates enables regulators to design effective policy instruments for mitigating market risk and assisting in making the financial system more stable.

4. Benefits to Institutional Investor and Fund Manager

   Institutional investors can use the findings of the study to make their strategies more accurate in times of high volatility. Fund managers can manage risks more effectively and capitalize on opportunities in times of market change by identifying when herding behavior dominates.

5. Contribution to Indian Market Studies

   With a focus on India's emerging stock market, the research helps to bridge the gap in the behavioral finance literature in emerging economies. The research presents new evidence of how herding behavior continues in India's special economic and market environment.

6. Improving Investor Education

   Through drawing attention to the influence of psychological biases like herding on investment decisions, this research is an input to investor education. Educating investors on such biases can result in better, more thought-out decisions and less spontaneous, herd-style decisions.

7. Longer-Term Impacts on Market Development

   With ongoing development of Indian financial markets, regulation and understanding of herding behavior are important to support long-term development. This research gives insights to design schemes to make markets more efficient, stable, and encourage investor participation.

CHAPTER 2
LITERATURE REVIEW

2.1 Overview of Herding Behavior

Herding is the tendency of investors to follow the behavior of others instead of using their analysis or information. Herding contradicts the Efficient Market Hypothesis (EMH), which assumes that asset prices reflect all available information because rational investors make rational decisions. Herding can result from informational cascades (Bikhchandani, Hirshleifer, & Welch, 1992), fear of reputation (Scharfstein & Stein, 1990), or psychological impacts resulting from fear and greed. Herding diverges from fundamentals to form bubbles during rising markets and crashes during falling markets.

During recent decades, especially after the global financial crises and the rapid financial market digitalization, scholars have been putting growing emphasis on capturing herding based on market-wide indicators, notably in emerging markets such as India.

2.2 CSAD and CSSD: Methods of Herding Detection

Early empirical research like Christie and Huang (1995) proposed the Cross-Sectional Standard Deviation (CSSD) as a metric to identify herding during times of market stress. They argued that under the assumption of herding, return dispersions would decline during market extremes. CSSD was subsequently criticized, however, as being outlier-sensitive and more appropriate to identify herding during times of extreme market movement.

To counteract these frailties, Chang, Cheng, and Khorana (2000) proposed an alternative: the Cross-Sectional Absolute Deviation (CSAD) approach

In contrast to CSAD, CSAD measures herding in all market states, not only stress. The CSAD model runs a cross-sectional average of absolute stock return deviations against market returns and the square of market returns. A negative coefficient on the squared term that is significant shows herding: as market returns become more extreme, dispersion does not rise proportionally but flattens or falls, which is indicative of collective movement.

In light of the capacity of CSAD to identify non-linear herding behavior under ordinary and extreme conditions, this study applies the CSAD method only.

2.3 Global Evidence on Herding Behavior

Research evidence using CSAD and other similar approaches has yielded mixed herding evidence in global markets:

1. Chang et al. (2000) further analyzed the equity markets of the U.S., Hong Kong, Japan, South Korea, and Taiwan. There was no herding in the developed countries like the U.S. and Hong Kong but the emerging countries of South Korea and Taiwan exhibited high herding

2. Zheng and Chiang (2010) extended this to an 18-country larger sample. They found herding in non-U.S. developed markets and stronger herding in Asian markets. They also found evidence of asymmetric herding — stronger during bull markets than bear markets, especially in Asia.

3. Wendi Chen (2020) experimented with Chinese A-share markets with CSAD for the period 2016–2019. The research established persistent herding in Shanghai and Shenzhen markets and detected a rising trend of herding intensity with time. Chen's research highlights that herding is not only crisis-based, but can be persistent even in relatively stable markets, increasing in intensity over time.

2.4 The Evidence of Indian Equity Market Herding

Indian equity markets have undergone tremendous change over the past two decades — ranging from regulatory reforms, deepening financialization, growth of mutual funds, to digitization of platforms. This provides a context for India to be a fertile ground for behavioral finance studies.

Some studies have directly investigated herding in the Indian context:

1. Prosad, Kapoor, and Sengupta (2012) applied both CSSD and CSAD methods on Nifty 50 data. They found limited herding overall but found significant herding in bull markets. The study concluded Indian markets are efficient overall, but herding occurs during optimistic times.

2. Lakshman, Basu, and Vaidyanathan (2013) tested herding asymmetry in India. They found that herding was stronger in the direction of the rising market than a falling market, consistent with the evidence from other emerging markets.

3. Panda and Nanda (2017), employing CSAD, confirmed the existence of intense herding behavior during bull and bear phases but even more forcefully during up markets.

4. Chakrabarti et al. (2020) contended that the Foreign Institutional Investors (FIIs) play a significant role in shaping herding in India. They argued in their study that the actions of FIIs reinforce price tendencies and generate feedback mechanisms in the market.

These studies show that Indian retail as well as institutional investors herd, especially in the presence of market optimism, uncertainty, or high volatility.

2.5 Determinants of Herding in India

Several unique elements make herding behavior particularly pronounced in India:

1. High Retail Participation: More retail investors, especially after 2020 as a result of COVID-19 lockdowns, have contributed to more herd-driven market activity.
2. Information Asymmetry: Regardless of greater financial literacy, most retail consumers continue to follow social media tips, headlines, and word-of-mouth, promoting imitation.
3. Institutional Pressures: India's mutual fund managers and portfolio managers also face peer-performance pressure, which results in institutional herding.

4. Macroeconomic Shocks: The 2008 Global Financial Crisis, demonetization in 2016, implementation of GST, and the COVID-19 pandemic caused huge inflows or outflows into equities.

These combined make India a rich and important setting to study how herding behavior emerges under different macroeconomic and market conditions.

2.6 Gaps in Current Literature

Though global and Indian studies have been informative, there have been some lacunae:

1. Most research has been brief (covering 3–5 years), examining individual crises only.
2. Few have considered explicitly long-term (more than twenty years) trends in herding behavior.
3. Industry-specific herding (tech, banking) is insufficiently studied.
4. Few studies have examined herding asymmetry in isolation during bull and bear markets over long horizons.
5. New trends like social media-activated herding remain to be widely researched in the Indian scenario.

Therefore, a comprehensive 20-year empirical analysis — on CSAD basis — of Indian equity markets, such as is attempted herein, is relevant as well as necessary.

2.7 Conclusion

The literature considered suggests that herding behavior is a common and multi-faceted phenomenon that can be seen even in developed markets but is more pronounced in developing markets like India. Although previous models such as CSSD provided the initial foundation, CSAD provides a stronger and more resilient model to identify normal and abnormal market conditions. The Indian market with its dynamic regulatory environment, heightened digitization, and heightened retail participation provides the best case to examine how herding behavior has evolved through major economic and financial events between 2005 and 2025. This review of literature not only signifies the significant theoretical and empirical advancements but also signifies the importance and methodological maturity of this research.

CHAPTER 3
RESEARCH METHODOLOGY

Introduction

This chapter outlines the methodology adopted in the analysis of herding behavior in the Indian equity market during a period of 20 years (2005–2025). The method has been developed to measure the presence and alterations of herding bias with daily stock prices and applying the CSAD model developed by Chang et al. (2000). This chapter presents the sources of data, choice of sample, variable calculation, tools of analysis, and the statistical techniques adopted in the analysis.

Research Methodology

The study is empirical and quantitative in nature and employs secondary data in studying investor behavior. It adopts a longitudinal time-series and cross-sectional design so that the trends over time and across different market settings are examined. It is exploratory and confirmatory in nature — attempting to ascertain the presence of herding as well as its variations at different time periods and market settings.

The analytical framework is based mainly on regression analysis with the Cross-Sectional Absolute Deviation (CSAD) model. The model examines non-linear associations between stock return dispersion and market returns as a herding measure.

Data Acquisition and Sampling Methodology

- **Data Source**

Data employed in this research is secondary data, in the form of daily closing prices of shares and index values for a 20-year period between January 2005 and March 2025. These data were obtained from ProwessIQ, a gigantic financial database constructed by the Centre for Monitoring Indian Economy (CMIE). ProwessIQ is referred to as a trusted source used typically for academic and financial research in India.

- **Sample Selection**

- Index Used: Nifty 50 Index, a representative market return measure.
- Stocks Chosen: 39 companies that have been a continuous member of the Nifty 50 index for the entire research duration (2005–2025).

The continuous inclusion of such factors guarantees that the sample is maintained free from cases of listing or delisting, hence eliminating any form of distortion of results due to stock turnover within the index.

Data Preparation and Variable Construction

- **Data Cleaning**

The raw data collected from ProwessIQ was imported into Microsoft Excel for cleaning and pre-processing. The cleaning involved:
- Removal of missing values as well as inactive trading days.
- Sustaining temporal parameter consistency across all securities.
- Authorizing and amending stock splits or corporate transactions, as appropriate.

- **Variable Computation**

The most significant variables constructed for regression analysis are:

- **Cross-Sectional Absolute Deviation (CSAD):**

For every trading day, CSAD was calculated using the formula presented by Chang et al. (2000):

$$CSAD_t = \frac{1}{N}\sum_{i=1}^{N}\left|R_{i,t} - R_{m,t}\right|$$

where:

- $R_{i,t}$ = Individual stock *i* return at time *t*
- $R_{m,t}$ = Return of Nifty 50 index at point in time *t*.
- N = Number of stocks in the sample (39)

- Market Return (Rm): Daily returns of Nifty 50 index were computed as:

$$R_{m,t} = \frac{P_t - P_{t-1}}{P_{t-1}}$$

- Independent Variables:

- **$|R_{m,t}|$:** Absolute market return
- **$R^2_{m,t}$:** Squared market return

Their computation was done with Excel functions on every trading day of the 20-year period.

Analytical Tools and Programs Used

The statistical tool employed in the current study applied the following instruments:

- **Microsoft Excel (for calculations and preprocessing):**
    - Data cleaning and management
    - Return computations
    - Construction of variables (CSAD, absolute and squared market returns)
    - Extreme market conditions regression analysis.
- **IBM SPSS Statistics (for regression analysis):**
    - Ordinary Least Squares (OLS) regression
    - Regression diagnostics and residual analysis
    - Segmented time period and market phase model fit

3.6 Model Specification

To examine herding behavior, the following regression model was estimated:

$$CSAD_t = \alpha + \beta_1 |R_{m,t}| + \beta_2 R^2_{m,t} + \epsilon_t$$

Where:

- α = Y-intercept
- **β_1 and β_2 =** Coefficients of the independent variables
- **ϵ_t = Error term.**

The main indicator of herding behavior is the size and direction of β_2
- A negative and statistically significant β_2 indicates herding because it indicates a decrease in CSAD under the influence of significant market movements.

Market Condition Segmentation

The regression exercise was conducted under five varying economic periods:
1. Pre-Crisis (2005–2007)
2. Global Financial Crisis (2008–2009)
3. Post-Crisis Recovery (2010–2019)
4. COVID-19 Pandemic (2020–June 2021)
5. Post-COVID Phase (July 2021–March 2025)

Throughout each of these stages, the information was further segmented into:

- **Bull Market Phases:** Long-term trends on the basis of Nifty 50 index movement.
- **Bear Market Phases:** Enduring downtrends.

The segmentation was conducted by examining price trends and return patterns for each interval.

Extreme Market Condition Analysis

Besides the overall regression analysis, extreme market conditions were examined on the basis of a 5% threshold criterion:

- **Extreme Up Market Days:** Top 5% of positive daily market returns.
- **Extreme Down-Market Days:** Lowest 5% of daily negative market returns.

Due to the small number of observations available in such a situation, Excel was used to pull out data points and run regression analysis directly.

Overview of Methodological Framework

Stage	Tool Used	Purpose
Data Collection	ProwessIQ	Obtaining historical price data
Data Cleaning & Preprocessing	Excel	Filtering, return computation, CSAD and variable calculation
Regression Analysis	IBM SPSS	OLS regression for overall and segmented market scenarios
Extreme Market Analysis	IBM SPSS	Regression under 5% and 1% up/down market days
Market Phase Identification	Excel	Segmenting bull and bear periods within each time frame

Methodological Approach Constraints

- The study assumes continuous membership of 39 stocks in the Nifty 50 index for 20 years.
- The outside variables affecting herding behavior (e.g., news, FII flows) have not been considered.
- OLS application assumes linearity in residuals, which is not indicative of nonlinear market trends.
- The 5% threshold for identifying extreme market conditions, while conventional, may overlook more nuanced herding behaviors that occur outside these defined extremes.

CHAPTER 4
DATA ANALYSIS

Herding accentuates market volatility, inhibits efficient price discovery, and helps form speculative bubbles, thereby increasing the susceptibility of the financial system. For the Indian stock market, herding has been associated with periods of increased volatility during major global turmoil, for example, the dot-com debacle, the 2008 global financial crisis, and the 2000s commodity bubble (Prechter, 2010). Being prone to undermining market efficiency, there is a need to study the prevalence and pattern of herding in the Indian stock market.

To determine the presence of herding, in this study the CCK (2000) model is employed to determine non-linear deviations in returns dispersion that may be indicative of herding. Market-wide herding is evaluated under varying market states of normal, bullish, bearish, and extreme movements using the Cross-Sectional Absolute Deviation (CSAD) approach.

The analysis bridges a wide range of 21 years between 2005 and 2025, allowing for a detailed understanding of herding behavior under different economic environments. The research period is broken down into five different phases for a more organized inquiry: Pre-Crisis (2005–2007), Global Financial Crisis (2008–2009), Post-Crisis Recovery (2010–2019), Pandemic COVID-19 (2020–June 2021), and Post-COVID Period (July 2021–March 2025). Financial crises are typically viewed as negative for economic stability and are known to increase the volatility of stock markets, even if the magnitude of effect varies with different periods of time (Garg & Jindal, 2014; Caporale et al., 2008). While such times of elevated uncertainty reduce investor rationality, investors become susceptible to behavioral biases like herding behavior. Keeping these five crucial phases of time as the context, this research endeavors to explore the trends and magnitude of herding behavior in the Indian stock market.

Determining the presence and analyzing the impact of herding in India

In order to analyze the evidence for herding behavior, CSAD methodology has been extensively used in different markets (Prosad et al., 2012; Chiang & Zheng, 2010; Chang et al., 2000). Chang et al. (2000) suggested that if there is herding behavior, then the dispersion of stock returns is less for individual stocks compared to the market return. In other words, CSAD will decline or increase at a decreasing rate with respect to market return. Thus, a negative and significant value of b2(defined by Equation 3) provides evidence of herding behavior in the stock market.

The descriptive statistics for the CSAD series and market return (Rmt) for the period April 2005 through March 2025 using Nifty 50 companies are given in Table 4.1. The mean of the market return is 0.000586, with a minimum of -0.1298, a maximum of 0.1774, and a standard deviation of 0.0133, indicating that there is a high volatility present in the Indian stock market. The mean value of CSAD is 0.0131 with a minimum of 0.0025 and a maximum of 0.0605.

Skewness and kurtosis values for Table 4.1 are included, in which CSAD displays a skewness of 2.291 and kurtosis of 10.085, meaning that the distribution is non-normal and is leptokurtic. For the market rate of return (Rmt), it is -0.057 for skewness and 13.718 for kurtosis, meaning that the distribution of returns is essentially symmetrical but is nevertheless leptokurtic. Jarque-Bera test statistics for CSAD as well as for Rmt, in addition to Kolmogorov-Smirnov and Shapiro-Wilk tests(Fig 1 and Fig 2), confirm non-normality for both series. In spite of the deviation from normality, the use of the Ordinary Least Squares (OLS) regression is valid as well as resilient on account of the large data set (Wooldridge, 2003). The central-limit theorem states that normality hypotheses become less important for larger data sets, thus the use of OLS regression for further analysis is well supported.

Table 4.1: Summary statistics of CSAD and R_{mt} in the Indian stock market

	Whole Period (2005-2025)		Before crisis (2005-2007)		During crisis (2008-09)		After the crisis (2010-2019)		Covid crisis (Jan 2020-June 2021)		Post Covid (July 2021-March 2025)	
Observations	**CSAD**	R_{mt}	**CSAD**	R_{mt}	**CSAD**	R_{mt}	**CSAD**	R_{mt}	**CSAD**	R_{mt}	CSAD	R_{mt}
Mean	0.13129	0.00058	0. 01456	0. 00174	0.02007	-0. 00002	0. 01211	0.00039	0. 01528	0. 00084	0. 01025	0. 00047
Min	0 .00252	-0.12980	0. 00479	-0. 0677	0. 00664	-0 .1220	0. 00310	-0.05915	0. 00425	-0 .1298	0 .00252	-0.05929
Max	0 .06057	0 .17744	0 .03828	0.06305	0 .06057	0. 17744	.03475	.05319	0 .04344	0 .08763	0.04685	0 .03362
SD	0. 00498	0. .013309	0 .00409	0 .01492	0. 00720	0. 0252	.00325	0 .00966	0 .00612	0 .01740	0 .00314	0 .00867
Skewness	2.291	-0 .057	1.593	-0 .400	1.742	.455	1.363	-0 .055	2.013	-1.393	2.594	-0 .561
Kurtosis	10.085	13.718	4.529	2.422	4.358	5.996	4.930	1.927	4.301	12.833	21.184	4.137
Jarque -Bera	25369.54798	38912.16638	881.5265523	186.9651	832.3096	749.4584	3276.832	384.6212	690.4744	2687.209	18452.53	712.7867

CSAD represents cross-sectional absolute deviation
Rmt represents the cross-sectional equally weighted average of all stock returns of N stocks
Source: Research Output

Figure 1

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
CSAD	.116	4962	.000	.840	4962	.000

a. Lilliefors Significance Correction

Source: Research Output

Figure 2

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Market	.082	4962	.000	.900	4962	.000

a. Lilliefors Significance Correction

Source: Research Output

The Augmented Dickey-Fuller (ADF) test is used to determine whether the CSAD and R_{mt} series are stationary. It is important to perform a stationarity test as the first step before carrying out a time-series analysis. The reason is explained by Gujarati (2003, 2011), who states that a non-stationary series can only be interpreted within the period under observation and is not generalizable to other times. Therefore, non-stationary data might not be of much practical use. In addition, regression analysis using non-stationary series can result in misleading or even spurious findings. The results of the ADF tests can be seen below.

Figure 3

Time Series Tests for Variable: CSAD

	Values
Test(2)	Phillips-Perron
Alternative Hypothesis(2)	Stationary
P-Value(2)	0.01
Note(2)	p-value smaller than printed p-value
Truncation Lag(2)	10
Test(3)	Augmented Dickey-Fuller
Alternative Hypothesis(3)	Stationary
P-Value(3)	0.01
Note(3)	p-value smaller than printed p-value
Truncation Lag(3)	17

Computations done by R package tseries

Time Series Tests for Variable: Market

	Values
Test(2)	Phillips-Perron
Alternative Hypothesis(2)	Stationary
P-Value(2)	0.01
Note(2)	p-value smaller than printed p-value
Truncation Lag(2)	10
Test(3)	Augmented Dickey-Fuller
Alternative Hypothesis(3)	Stationary
P-Value(3)	0.01
Note(3)	p-value smaller than printed p-value
Truncation Lag(3)	17

Computations done by R package tseries

Source: Research Output

From the above test results, we can conclude that both the CSAD and R_{mt} series are Stationary(p-value = 0.01), thereby rejecting the null hypothesis, i.e., non-stationary series. In other words, the series does not follow a unit root. Therefore, the series' stationarity has fulfilled the OLS regression's underlying requirement.

Herding in Indian Stock Market as a whole

The CSAD regression analysis by Chang, Cheng, and Khorana (2000) provides valuable evidence on herding behaviour during various phases of the Indian stock market between the years 2005-2025. A negative, statistically significant coefficient of the squared market return term (b2) by this model is a sign of herding behaviour since it implies that investors override their own beliefs and imitate the consensus of the market. The results show that herding was present strongly only during the period of Covid-19 crisis (January 2020 – June 2021) where the b2 was negative and significant (-0.936). This implies that, under extreme uncertainty and high volatility, investors might have ignored firm-specific information to imitate the market. The results agree with Bouri et al. (2021) and Kizys et al. (2021) who discovered similar evidence of herding behaviour throughout the pandemic period for emerging and world markets citing panic sweeping across the markets and information asymmetry as a cause thereof, and Prosad et al. (2012) and Dhall & Singh (2020) validating the existence of herding behaviour during crisis or stress time in the Indian stock market.

Conversely, there was no statistically significant evidence of herding during the 2008-2009 global financial crisis. While financial stress typically heightens the possibility of herding, the non-significance of the period's b2 coefficient can be explained by extremely divergent investor reactions, representing extreme uncertainty and varying expectations about the revival of the market. These findings are consistent with the outcomes of Chiang and Zheng (2010), who reported composite herding behaviour during crises across markets was mixed. During the pre-crisis period (2005-2007) and post-crisis period (2010-2019, as well as between the months of July 2021 and March 2025), the b2 coefficients were not merely positive but were also significant (3.353, 4.061, 7.099 respectively), signifying a return to rational asset pricing behaviour. Investors during these periods were most likely to depend on firm fundamentals and individual analysis, rather than following collective trading behaviour.

In total, the research reaffirms that herding behaviour in the Indian stock market is context-dependent and episodic, appearing most noteworthily during times of unprecedented uncertainty like the Covid-19 pandemic. This aligns with previous research by Christie and Huang (1995), who claimed that herding is only present under stressful market situations but not for all crisis situations. Lack of herding during other times reflects enhanced maturity on the part of the Indian capital market as well as potentially better access to information and investment tools. The results reinforce the need for greater regulatory supervision as well as investor education, particularly during crisis times, to avert irrational movement of the market based on behavioural biases.

Table 4.2: Regression outcome for CSAD and market return in Indian stock market

$$CSAD_t = \alpha + b_1|Rm_t| + b_2R^2m_t + e_t$$

Variable	Whole Period (2005-2025)	Before crisis (2005-2007)	During crisis (2008-09)	After the crisis (2010-2019)	Covid crisis (Jan 2020 - June 2021)	Post Covid Crisis (July 2021 – March 2025)
α	0.011	0.013	0.016	0.011	0.012	0.009
b1	0.290	0.076	0.222	0.102	0.360	0.048
b2	0.247	**3.353**	0.315	**4.061**	**-0.936**	**7.099**

$CSAD_t$ represents cross-sectional absolute deviation calculated at time t
Rmt represents the cross-sectional equally weighted average of all stock returns of N stocks at time t,
|Rmt| is the absolute value of market return, and
R^2mt denotes the square of |Rmt|
Source: Research Output

Herding in the Bull and Bear Phase of the Market

The CSAD regression findings from Table 4.3 show the incidence of herding behaviour within the Indian stock market under both bull (positive returns) and bear (negative returns) market situations. The CSAD theory by Chang et al. (2000) states that herding is confirmed by a negative and significant b2 coefficient. But the findings do not show evidence of herding for both bull and bear markets throughout most time frames. During the bull market period (Panel A), even if some phases like pre-crisis (2005–2007) and post-crisis (2010–2019) show significant b2 coefficients (4.725 and 7.078, respectively), their positive signs confirm rational market behaviour over herding behaviour. This means investors were responding individually to information, particularly during the post-crisis growth conditions, thus supporting evidence by Christie and Huang (1995), who state that herding is not likely under stable or bullish market situations.

By contrast, Panel B of bear market situations shows no significant negative coefficients of b2, which reflects a lack of directional herding even under stressed times such as the Covid crisis (−0.368, not significant). While we do see a large significant positive post-Covid bear market coefficient of 7.877, it signifies dispersion rather than convergence of investor behaviour. These results contradict the directional herding hypothesis under which investors are more likely to herd under downturns under fear and uncertainty (Tan et al., 2008). Rather, we see that the Indian market is resilient and rational under both upward and downward movements, which may signal improvement in market transparency, financial literacy, and participation of institutional investors. Overall, whereas herding was present in previous aggregate-level findings throughout the Covid-19 crisis (illustrated by Table 4.2), the bull-bear breakdown in Table 4.3 identifies that this behaviour was not one-sided—it was not clearly evident throughout rising as well as falling markets. This implies event-oriented factors like the pandemic might have caused transient collective behaviour, but market direction was not a sufficient criterion for herding to happen. These findings are only partially supported by international evidence by Bouri et al. (2021) and Kizys et al. (2021), who reported directional herding under pandemic uncertainty, but rather draw attention to a more intricate, context-dependent behavior within the Indian stock market.

Table 4.3: Regression outcome for CSAD and market return in Indian stock market in bull and bear phase

$$CSAD_t^{BL} = \alpha + b1^{BL}|R_{mt}^{BL}| + b2^{BL}(R^2_{mt}{}^{BL}) + \varepsilon_t \qquad R_{mt} > 0$$
$$CSAD_t^{BR} = \alpha + b1^{BR}|R_{mt}^{BR}| + b2^{BR}(R^2_{mt}{}^{BR}) + \varepsilon_t \qquad R_{mt} < 0$$

Panel A			**Bull Market**			
Variable	**Whole Period (2005-2025)**	**Before crisis (2005-2007)**	**During crisis (2008-09)**	**After the crisis (2010-2019)**	**Covid crisis (Jan 2020 - June 2021)**	**Post Covid Crisis (July 2021 – March 2025)**
α	0.010	0.013	0.016	0.011	0.011	0.009
b1	0.328	0.072	0.237	0.058	0.383	0.151
b2	0.145	**4.725**	0.189	7.078	0.584	2.495

Panel B			**Bear Market**			
Variable	**Whole Period (2005-2025)**	**Before crisis (2005-2007)**	**During crisis (2008-09)**	**After the crisis (2010-2019)**	**Covid crisis (Jan 2020 - June 2021)**	**Post Covid Crisis (July 2021 – March 2025)**
α	0.011	0.013	0.015	0.011	0.013	0.010
b1	0.254	0.068	0.199	0.132	0.247	0.022
b2	0.335	2.401	0.626	1.608	-0.368	**7.877**

$CSAD_t^{BL}$ represents cross-sectional absolute deviation calculated in the bull market
Rmt^{BL} represents the cross-sectional equally weighted average of all stock returns of N stocks at time t in the bull market,
$|Rmt^{BL}|$ is the absolute value of market return in the bull market, and
R^2mt^{BL} denotes the square of |Rmt| in the bull market
$CSAD_t^{BR}$ represents cross-sectional absolute deviation calculated in the bear market
Rmt^{BR} represents the cross-sectional equally weighted average of all stock returns of N stocks at time t in the bear market,
$|Rmt^{BR}|$ is the absolute value of market return in the bear market, and
R^2mt^{BR} denotes the square of |Rmt| in the bear market
Source: Research Output

Herding in the Extreme Up and Down Markets

In times of high market stress, the literature indicates that, to seek reassurance and to escape the discomfort of having to make personal decisions in the face of uncertainty, investors have a tendency to follow the crowd and hence herding is usually an outcome of such action. This study examines the prevalence of herding in times of extreme up and extreme down markets. Regression estimates for extreme market conditions based on 5% and 1% cut-off values are given in Tables 4.4 and 4.5, respectively. Extreme down markets are returns in the bottom 5% (or 1%) of market return distribution, and extreme up markets are returns in the upper 5% (or 1%) of distribution.

As evident in Table 4.4 (Panel A), the whole period (2005–2025) [b2=−0.954] coefficient b2 is not statistically significant and is negative but does not represent conclusive evidence of herding during extreme down-market conditions for the entire period. Nevertheless, Table 4.4 (Panel A) yields a significantly positive b2 in the post-Covid period (July 2021–March 2025) [b2=12.992] and indicates the lack of herding behaviour under extreme down-market conditions during the post-pandemic recovery phase. Table 4.4 (Panel B) shows that there is a significantly negative b2 for the entire period (2005–2025) [b2=−1.781] in the extreme up market and confirms the presence of herding during extreme upward movements in the Indian stock market.

Table 4.4: Regression outcome for CSAD and market return in Indian stock market in extreme up and extreme down market (5% criteria)

$CSAD_t^{BL} = \alpha + b1^{UP}|Rm_t^{BL}|\,|*D_t^{BL} + b2^{BL}(R^2m_t^{\,BL})*D_t^{BL} + \varepsilon_t$ $\quad R_{mt} > 0$

$CSAD_t^{BR} = \alpha + b1^{BR}|Rm_t^{BR}|*D_t^{BR} + b2^{\,BR}(R^2m_t^{\,BR})*D_t^{BR} + \varepsilon_t$ $\quad R_{mt} < 0$

Panel A **Extreme down market**

Variable	Whole Period (2005-2025)	Before the crisis (2005-2007)	During the crisis (2008-09)	After the crisis (2010-2019)	Covid crisis (Jan 2020 – June 2021)	Post Covid Crisis (July 2021 – March 2025)
α	0.009	0.015	0.023	0.011	0.021	0.015
b1	0.384	0.022	0.051	0.124	-0.002	-0.348
b2	-0.954	2.577	1.165	1.219	1.096	**12.992**

Panel B **Extreme upmarket**

Variable	Whole Period (2005-2025)	Before crisis (2005-2007)	During crisis (2008-09)	After the crisis (2010-2019)	Covid crisis (Jan 2020 – June 2021)	Post Covid Crisis (July 2021 – March 2025)
α	0.004	0.011	0.008	0.011	-0.004	0.016
b1	0.626	0.219	0.530	0.016	1.241	-0.529
b2	**-1.781**	2.437	-1.367	8.072	-8.242	17.761

$CSAD_t^{BL}$ represents cross-sectional absolute deviation calculated in the bull market
Rmt^{BL} represents the cross-sectional equally weighted average of all stock returns of N stocks at time t in the bull market,
$|Rmt^{BL}|$ is the absolute value of market return in the bull market, and
R^2mt^{BL} denotes the square of |Rmt| in the bull market
$D_t^{BL} = 1$, if the market return on day t falls in the extreme 5% upper tail of the market return distribution, else 0 $CSAD_t^{BR}$ represents cross-sectional absolute deviation calculated in the bear market
Rmt^{BR} represents the cross-sectional equally weighted average of all stock returns of N stocks at time t in the bear market,
$|Rmt^{BR}|$ is the absolute value of market return in the bear market, and
R^2mt^{BR} denotes the square of |Rmt| in the bear market
$D_t^{BR} = 1$, if the market return on day t falls on the extreme 5% lower tail of the market return distribution, else 0
Source: Research Output

Alternatively, Table 4.5 (Panel A), based on a stricter 1% criterion, also indicates that although the entire sample period coefficient b2 (2005–2025) [b2=−1.016] is negative, it is not significant, which again confirms no significant herding in the entire sample period. But a significantly positive b2 from the post-Covid period (July 2021–March 2025) [b2=79.980] again confirms a lack of herding in extreme down markets in the post-pandemic period. Table 4.5 (Panel B) also indicates a significantly negative b2 from the Covid Crisis period (Jan 2020–June 2021) [b2=−11.343] during the extreme up market, indicating increased herding activity during pandemic-led market booms.

Table 4.5: Regression outcome for CSAD and market return in Indian stock market in extreme up and extreme down market (1% criteria)

$CSAD_t^{BL} = \alpha + b1^{UP}|R_{mt}^{BL}| * D_t^{BL} + b2^{BL}(R^2_{mt}{}^{BL}) * D_t^{BL} + \varepsilon_t$ $\qquad R_{mt} > 0$

$CSAD_t^{BR} = \alpha + b1^{BR}|R_{mt}^{BR}| * D_t^{BR} + b2^{BR}(R^2_{mt}{}^{BR}) * D_t^{BR} + \varepsilon_t$ $\qquad R_{mt} < 0$

Panel A **Extreme down market**

Variable	Whole Period (2005-2025)	Before crisis (2005-2007)	During crisis (2008-09)	After the crisis (2010-2019)	Covid crisis (Jan 2020 – June 2021)	Post Covid Crisis (July 2021 – March 2025)
α	0.009	-0.176	0.102	0.013	-0.002	0.120
b1	0.386	7.256	-1.785	0.029	0.216	-5.989
b2	-1.016	-63.568	10.995	2.552	0.906	**79.980**

Panel B **Extreme upmarket**

Variable	Whole Period (2005-2025)	Before crisis (2005-2007)	During crisis (2008-09)	After the crisis (2010-2019)	Covid crisis (Jan 2020 – June 2021)	Post Covid Crisis (July 2021 – March 2025)
α	0.007	-0.220	0.125	0.029	-0.035	0.018
b1	0.545	9.421	-1.773	-0.833	1.884	-1.164
b2	-1.425	-86.884	7.916	17.869	**-11.343**	36.416

$CSAD_t^{BL}$ represents cross-sectional absolute deviation calculated in the bull market
Rmt^{BL} represents the cross-sectional equally weighted average of all stock returns of N stocks at time t in the bull market,
$|Rmt^{BL}|$ is the absolute value of market return in the bull market, and
R^2mt^{BL} denotes the square of |Rmt| in the bull market
D_t^{BL} = 1, if the market return on day t falls in the extreme 1% upper tail of the market return distribution, else 0
$CSAD_t^{BR}$ represents cross-sectional absolute deviation calculated in the bear market
Rmt^{BR} represents the cross-sectional equally weighted average of all stock returns of N stocks at time t in the bear market,
$|Rmt^{BR}|$ is the absolute value of market return in the bear market, and
R^2mt^{BR} denotes the square of |Rmt| in the bear market
D_t^{BR} =1, if the market return on day t falls on the extreme 1% lower tail of the market return distribution, else 0
Source: Research Output

CHAPTER 5
CONCLUSION, LIMITATIONS AND FUTURE SCOPE

This research tested the prevalence, patterns, and dynamics of herding behavior among Indian equity market investors across a broad 20-year span between 2005 and 2025. Through the Cross-Sectional Absolute Deviation (CSAD) method, this research conducted an extensive, empirical analysis of how herding in collective action arises under different market regimes, crises, and phases of economic transition.

Key Findings

The analysis uncovered the following key points:

- Episodic Herding Behavior: Herding was not characteristic of the Indian equity market in all the durations. Rather, it manifested episodically, particularly under circumstances of extreme uncertainty. Interestingly, extreme herding was observed during the COVID-19 pandemic period (January 2020–June 2021), when there was record-breaking volatility, panic, and information asymmetry. The b_2 coefficient for the period was highly negative, confirming the prevalence of herd behavior when panic and uncertainty prevailed.

- Absence of Herding in Other Crises: Notably, in the Global Financial Crisis (2008–2009) — yet another period of acute stress — no significant evidence of herding existed. This deviation is a reflection that all crises do not bring forth identical behavioral reactions, and that investor conduct may vary depending on the personality, duration, and perceived impact of exogenous shocks.

- Normal Market Conditions and Rational Behavior: Under the pre-crisis phase (2005–2007), the post-crisis recovery phase (2010–2019), and the post-COVID phase (2021–2025), the Indian market was behaving according to rational asset pricing theories. Positive and significant b_2 coefficients indicated that the investors behaved independently, depending more on firm fundamentals rather than crowd-following.

- Herding in Periods of Extreme Market: Herding was found to be more pronounced in periods of extreme up-market conditions, particularly during the COVID-19 pandemic. In top 5% and top 1% extreme positive return days, there was statistically significant herding evidence. In periods of extreme down markets, herding was not present or was mixed.

- Bull vs Bear Market Phases: To the contrary of widespread belief that herding is more pronounced in bear (falling) markets, no evidence of herding was observable in either bull or bear phases in this research. This suggests that crises can be an impulse for collective behavior, but underlying market trends (rise or fall) are inadequate impulses for imitation en masse.

Major Limitations

Even though the study has insightful comments, it is also prone to some shortcomings:

- Sample Restraint: The sample was limited to 39 Nifty 50 stocks that were traded regularly over 20 years. Although this provided consistency, it excluded stocks that entered or exited the index, potentially missing key behavioral dynamics in mid-cap and small-cap segments.

- Restricted Sample for Retail-Driven Trading: A considerable majority of retail investor trading in India is in the mid-cap and small-cap segment, and those were not part of this research. The findings, therefore, might not indicate the herding behavior in the entire universe of retail investors wherein the behavioral biases could be even more intense.

- Price Data Only: Estimation was conducted with only price and return data, excluding macro variables (e.g., interest rates, inflation) or investor-level sentiment indexes that might further account for variation in herding behavior.

- Use of CSAD in Isolation: Even if CSAD is strong and universally well-received, herding can be modeled with other forms of models including time-varying parameter models, entropy-based measures, or agent-based simulations, which can possibly mimic more sophisticated dynamics.

- Extreme Market Definitions: Extreme markets were defined in terms of top/bottom 5% and 1% of returns. While this is standard, it is perhaps naive in the sense of the nature of financial distress or exuberance, and does not capture more subtle herding below these thresholds.

- No Distinction among Investor Types: Institutional and retail investors were not distinguished in the research. Due to their different information availability and behavior characteristics, individual analysis might provide more fruitful results.

Future Scope of Research

From the findings and limitations, some lines of future research are clear:

- Sectoral Herding Analysis: Future studies can be focused on sectoral herding, especially in industries like technology, banking, and infrastructure, where the likelihood of herding is higher.

- Investor Segmentation: Segmentation of herding between retail and institutional investors may render further inferences more reasonable, particularly in the context of growing retail participation's relevance post-2020.

- Impact of Web Platforms and Social Media: Even with greater opportunities created due to online trading cultures, auto-trading, and investment guides written by experts, future studies will analyze how web platforms are re-constituting Indian herd behavior.

- Behavioral Dynamics of Policy Change Announcement: Further research would establish if policy decisions made abruptly (e.g., demonetization, budget announcement) affect aggregative investor sentiment in the short term and long term.

- Advanced Modeling Techniques: Employing more sophisticated econometric techniques like machine learning software, structural break models, or sentiment analysis software would improve the identification and forecasting of herding.

- International Comparisons: Cross-country comparisons of India with other emerging or developing nations can identify the channels through which cultural, institutional, and regulatory variables affect herding behavior.

Recommendations for reducing herding bias in Indian equity markets

Guided by 20-year empirical Nifty 50 index herding 2005–2025, the following evidence-based measures are suggested for counteracting irrational collective action as well as for promoting market stability:

1. Foster Investor Education and Awareness

- Targeted Training Programs: Implement investor training programs promoting consciousness regarding the risks of herd mentality, especially during situations of crisis such as the COVID-19 situation when the highest incidences of herding were prevalent. The training should focus on cognitive biases, as well as the importance of independent decision-making.
- Digital literacy campaigns: Educate retail investors how to critically analyze social trends on social media as well as avoid "Fear of Missing Out" (FOMO) trades, which drove the herding during the period of the pandemic.

2. Enhance Market Transparency and Accessibility of Information

- Transparency of real-time information: Eliminate asymmetry of information through mandatory uniform, real-time disclosure of activities of institutional investors (i.e., FII/FPI transactions) in order not let retail investors blindly chase "smart money" perceived.
- Sector-Specific Risk Warnings: Regulators such as SEBI need to issue frequent signals in respect of those sectors that exhibit tendencies of herding (e.g., infra, tech) from CSAD-based risk thresholds.

3. Regulatory Interventions in Crisis Episodes

- Dynamic Circuit Breakers: Activate volatility-based trading halts in times of excessive market volatility (top/bottom 5% returns) as in the COVID-19 event in an attempt to temper panic-driven herding.
- Stress-Test Frameworks: Mandate institutional investors to mirror conditions of herding in risk models, maintaining buffer of liquidity in systemic shocks.

4. Encourage Fundamental Analysis Over Speculation

- Long-Term Holdings Incentives through Taxes: Offer capital tax rebates for 3-year+ holdings with the aim of disincenting short-term trading created through herds.
- Preventive Algorithmic Trading Safeguards: Require public exposure of algo-strategies that contribute to heightened herding (i.e., momentum followers) for the elimination of reflexive distort.

5. Institutional Changes for Decentralizing Market Power

- Retail Investor Syndicates: Create co-operative environments for retail investors to syndicate their capital for fundamentals-based analysis in an effort not to rely overmuch on instincts of the herd.
- Diversified Benchmarking: Transition from focus on Nifty 50 towards bigger indexes (i.e., Nifty 500) in an effort to move away from both concentration risk as well as sectoral herding.

6. Advanced Monitoring Systems

- Sentiment Analysis Tools: Develop AI-driven systems for monitoring social media/investment forum discussions for narrative control with early alerts.
- CSAD-based early warning signs: Add Cross-Sectional Absolute Deviation measures for SEBI's monitoring system in an attempt to detect anomalous patterns of dispersal.

Implementation Framework

Initiative	Responsible Stakeholder	Timeline
Investor Bias Workshops	SEBI + Stock Exchanges	6–12 Months
Crisis Circuit Breakers	SEBI	Immediate
Tax Reform Advocacy	Ministry of Finance	12–18 Months
Herding Risk Dashboards	Brokerage Firms	6 Months

REFERENCES

1. Chang, E. C., Cheng, J. W., & Khorana, A. (2000). An examination of herd behavior in equity markets: An international perspective. *Journal of Banking & Finance*, *24*(10), 1651–1679. https://doi.org/10.1016/s0378-4266(99)00096-5
2. Chen, W. D. (2020). An Examination of Herding Behavior in Chinese A-Share Market by Cross-Sectional Absolute Deviation (CSAD). *Modern Economy, 11*, 785-792. https://doi.org/10.4236/me.2020.114058
3. Devenow, A., & Welch, I. (1996). Rational herding in financial economics. *European Economic Review*, 40(3–5), 603–615. https://doi.org/10.1016/0014-2921(95)00073-9
4. Graham, J. R., & Harvey, C. R. (2001). The theory and practice of corporate finance: evidence from the field. *Journal of Financial Economics*, 60(2–3), 187–243. https://doi.org/10.1016/s0304-405x(01)00044-7
5. Hirshleifer, D. (2001). Investor psychology and asset pricing. *Journal of Finance, 56*(4), 1533-1597. https://doi.org/10.1111/0022-1082.00379
6. Kumar, A., & Goyal, A. (2017). Investor behavior in the Indian stock market: A study on herding. *The Indian Journal of Economics, 98*(2), 15-30.
7. Hirshleifer, D. (2001). Investor Psychology and Asset Pricing. *The Journal of Finance, 56(4),* 1533-1597. https://doi.org/10.1111/0022-1082.00379
8. Goriaev, A., Nijman, T. E., & Werker, B. J. (2007). Performance information dissemination in the mutual fund industry. *Journal of Financial Markets, 11*(2), 144–159. https://doi.org/10.1016/j.finmar.2007.10.003
9. Bikhchandani, S., & Sharma, S. (2001). Herd behavior in financial markets. *IMF Staff Papers, 47(3),* 279-310.
10. Abhijit V. Banerjee, A Simple Model of Herd Behavior, *The Quarterly Journal of Economics*, Volume 107, Issue 3, August 1992, Pages 797–817, https://doi.org/10.2307/2118364
11. Vissing-Jorgensen, A. (2003). Perspectives on Behavioral Finance: Does “Irrationality” Disappear with Wealth? Evidence from Expectations and Actions. *NBER Macroeconomics Annual, 18,* 139–194. https://doi.org/10.1086/ma.18.3585252

12. Chiang, T. C., & Zheng, D. (2010). An empirical analysis of herd behavior in global stock markets. *Journal of Banking & Finance, 34(8),* 1911–1921. https://doi.org/10.1016/j.jbankfin.2009.12.014
13. Prosad, J. M., Kapoor, S., & Sengupta, J. (2012). An examination of herd behavior: An empirical evidence from Indian equity market. *International Journal of Trade, Economics and Finance,* *3*(2), 154–157. https://doi.org/10.7763/IJTEF.2012.V3.190
14. Christie, W.G. and Huang, R.D. (1995) Following the Pied Piper: Do Individual Re-turns Herd around the Market? *Financial Analysts Journal,* ***51****, 31-37*. https://doi.org/10.2469/faj.v51.n4.1918

FINAL DOCUMENT.docx

Delhi Technological University

Document Details

Submission ID

trn:oid:::27535:96009973

Submission Date

May 15, 2025, 1:09 PM GMT+5:30

Download Date

May 15, 2025, 1:10 PM GMT+5:30

File Name

FINAL DOCUMENT.docx

File Size

438.8 KB

55 Pages

12,819 Words

74,307 Characters

7% Overall Similarity

The combined total of all matches, including overlapping sources, for each database.

Filtered from the Report

- Bibliography
- Quoted Text
- Cited Text
- Small Matches (less than 10 words)

Match Groups

59 Not Cited or Quoted 7%
Matches with neither in-text citation nor quotation marks

0 Missing Quotations 0%
Matches that are still very similar to source material

0 Missing Citation 0%
Matches that have quotation marks, but no in-text citation

0 Cited and Quoted 0%
Matches with in-text citation present, but no quotation marks

Top Sources

4% Internet sources
2% Publications
5% Submitted works (Student Papers)

Integrity Flags

0 Integrity Flags for Review

No suspicious text manipulations found.

Our system's algorithms look deeply at a document for any inconsistencies that would set it apart from a normal submission. If we notice something strange, we flag it for you to review.

A Flag is not necessarily an indicator of a problem. However, we'd recommend you focus your attention there for further review.

Match Groups

59 Not Cited or Quoted 7%
Matches with neither in-text citation nor quotation marks

0 Missing Quotations 0%
Matches that are still very similar to source material

0 Missing Citation 0%
Matches that have quotation marks, but no in-text citation

0 Cited and Quoted 0%
Matches with in-text citation present, but no quotation marks

Top Sources

4% Internet sources
2% Publications
5% Submitted works (Student Papers)

Top Sources

The sources with the highest number of matches within the submission. Overlapping sources will not be displayed.

1	Internet	
dspace.dtu.ac.in:8080		<1%
2	Submitted works	
National College of Ireland on 2019-08-20		<1%
3	Internet	
i-scholar.in		<1%
4	Internet	
www.doria.fi		<1%
5	Internet	
www.coursehero.com		<1%
6	Submitted works	
University of Witwatersrand on 2017-03-28		<1%
7	Internet	
acearchive.org		<1%
8	Submitted works	
The French - Vietnamese Center for Management Education on 2024-10-19		<1%
9	Publication	
Ved Prakash, K. Padmasree, Sarwdaman Kashyap. "Existence of Herding Behavio...		<1%
10	Internet	
5dok.net		<1%

11	Internet	
www.mdpi.com		<1%
12	Internet	
www.studymode.com		<1%
13	Submitted works	
University of Bristol on 2020-04-19		<1%
14	Internet	
repositorium.uminho.pt		<1%
15	Publication	
Natalia Alves Tavares, Paulo Vitor Jordão da Gama Silva, Marcelo Cabus Klotzle. "I...		<1%
16	Submitted works	
National Research University Higher School of Economics on 2022-05-17		<1%
17	Submitted works	
University of Edinburgh on 2025-04-10		<1%
18	Submitted works	
University of Hull on 2016-01-09		<1%
19	Submitted works	
Heriot-Watt University on 2023-04-11		<1%
20	Submitted works	
Institut Teknologi Brunei on 2021-08-18		<1%
21	Submitted works	
Westminster International University in Tashkent on 2019-04-04		<1%
22	Submitted works	
American University in the Emirates on 2016-02-07		<1%
23	Submitted works	
Bocconi University on 2022-11-07		<1%
24	Submitted works	
ESC Rennes on 2023-10-31		<1%

25 Submitted works

University of Belgrade on 2021-03-08 <1%

26 Submitted works

Vrije Universiteit Amsterdam on 2024-11-27 <1%

27 Internet

journal-archieves8.webs.com <1%

28 Internet

research-api.cbs.dk <1%

29 Publication

Anna Zalewska, Yue Zhang. "Mutual funds' exits, financial crisis and Darwin", Jour... <1%

30 Submitted works

B.S. Abdur Rahman University on 2014-04-05 <1%

31 Submitted works

Bocconi University on 2024-05-29 <1%

32 Submitted works

The Robert Gordon University on 2012-04-14 <1%

33 Submitted works

University of Birmingham on 2025-04-07 <1%

34 Submitted works

University of Glasgow on 2023-08-23 <1%

35 Submitted works

Vietnamese-German University on 2015-10-01 <1%

36 Internet

pdfcoffee.com <1%

37 Internet

sci-hub.se <1%