A Study on the Impact of Herding Behavior on the Indian Stock Market

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DECLARATION BY STUDENT

I hereby declare that the data presented in this Dissertation report entitled, "**A Study On the Impact of Herding Behavior On the Indian Stock Market**" is based on the results of investigations carried out by me in the Commerce Discipline at the Goa Business School, Goa University under the Supervision of Mrs Aakruthi Alarnkar and the same has not been submitted elsewhere for the award of a degree or diploma by me. Further, I understand that Goa University or its authorities will be not be responsible for the correctness of observations experimental or other findings given the dissertation.I hereby authorize the University authorities to upload this dissertation on the dissertation repository or anywhere else as the UGC regulations demand and make it available to any one as needed.

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COMPLETION CERTIFICATE

This is to certify that the dissertation report **"A Study on the Impact of Herding Behavior on the Indian Stock Market"** is a bonafide work carried out by Mr. Nabisab Dawal Bagwan under my supervision in partial fulfilment of the requirements for the award of the degree of Masters of Commerce in the Discipline Commerce at the Goa Business School, Goa University

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CONTENTS

LIST OF TABLES

ABBREVIATIONS USED

Entity	Abbreviation
Fast Moving Consumer Goods	FMCG
Information Technology	IT
National Stock Exchange	NSE
Cross Sectional Absolute Deviation	CSAD
Efficient market Hypothesis	EMH
Capital Asset Pricing Model	CAPM
Modern Portfolio Theory	MPT
Bombay Stock Exchange	BSE
Stock Exchange Sensitive Index	SENSEX
National Securities Depository Limited	NSDL
Calcutta Stock Exchange	CSE
Metropolitan Stock Exchange	MSE
India International Exchange	India INX
Exchange Trade Funds	ETFs
Global Financial Crisis	GFC
Eurozone Crisis	EZC
Arbitrage Pricing Theory	APT
United States	US
Brazil, Russia, India, China & South Africa	BRICS
Smooth Transition Regression	STR
Gulf Cooperation Council	GCC
Foreign Institutional Investor	FII
Multifractal Detrended Fluctuation Analysis	MFDFA
Price Earning	P/E ratio
Augmented Dickey-Fuller	ADF
Phillips-Perron	PP
Chang Cheng Khorana Model	CCK Model

Christie Huang Model	CH Model
Cross Sectional Absolute Deviations	CSAD
Cross Sectional Standard Deviations	CSSD

A Study On the Impact of Herding Behavior On the Indian Stock Market

Preface:

The concept of herding behavior in the Indian stock market is examined in this dissertation, with a particular emphasis on sectoral indices like Nifty energy, Nifty financial services Nifty Auto, Nifty FMCG, and Nifty IT and broad indices like Nifty 50, Nifty Midcap 50, Nifty Smallcap 50 that are listed on the National Stock Exchange (NSE). The analysis uses daily stock and indices prices from the NSE website and the study period covers 2016 to 2023. To ascertain if herding behavior occurs and what its impacts are in various market sectors, the study makes use of regression analysis and the Cross-sectional Absolute Deviation (CSAD) technique developed by Chang et al. (2000). The findings indicate that although certain broad indices such as the Nifty 50, Nifty Midcap 50, and Nifty Small cap 50, exhibit no noticeable herding behavior, others have a more intricate pattern. Sectoral indices such as Nifty Auto, Nifty FMCG, and Nifty IT do not have any herding behavior; however, Nifty Financial Services and Nifty Energy do show significant herding.

Key Words:

Herding Behavior, Indian stock market, Broad indices, Sectoral indices, Cross-sectional Absolute Deviation (CSAD)

CHAPTER 1: INTRODUCTION TO HERDING, STOCK MARKET AND INDICES

1. INTRODUCTION

This chapter discusses the background of the study and how limitations of standard financial theories gave way to a new field of finance known as Behavioural Finance which is based on an investor's psychology and emotional biases. In the way it discusses the basics of Indian stock market, National Stock Exchange (NSE) and its indices, It also lays a base for various standard financial theories such as Efficient market Hypothesis (EMH), Capital Asset Pricing Model (CAPM), Modern Portfolio Theory (MPT). It also discusses herding behavior with specifications to the study

1.1 BACKGROUND

The study focuses on Herd Behavior, where investors mimic each other's actions while making investments and ignore their knowledge, opinions, and information. However, if given an option, they might not select the same option if told individually. There may be various reasons why people resort to herd behaviour. First is the desire of people to be socially acceptable and confirmed by a group. No one wants to be an outcast. Second, is the common perception of people that such a large group cannot be wrong about a decision. So, although at a personal level, one might doubt the group's decision he/she will still follow the herd as they think that the group might know something that he/she doesn't know. Herd behavior is also seen when without looking at the fundamentals of the stock, the investors respond to sell or buy to the slightest of information in the market. (Kanojia et al., 2022) The "herd" instinct is a mentality characterized by the lack of individual decision-making or thoughtfulness, causing people to think and act in the same way as the majority of those around them. An overwhelming number of individuals across the world follow others in financial decision-making. Research shows that investors herd in stock markets. When investors herd, they tend to trade in the same direction in a short time and ignore their private information, as individuals might be better off when they follow the trades of preceding investors. There is a common belief among the social psychologists that investors follow each other to feel confident in their investment decision-making (Sitkin and Pablo, 1992). an efficient financial market is one where investors make rational decisions, and stock prices reflect all available information, remaining unpredictable over time (Fama, 1970). (Economou et al., 2011) advocate that herding threatens financial stability, thereby exposing market participants and financial institutions to unchangeable systemic risk. There are a series of reasons why herding behavior in financial markets is worth examining and documenting. From a regulatory perspective, correlated patterns of trade may well undermine financial stability. (Khan & Suresh, 2022) Herd behavior usually produces enormous levels of volatility in the stock markets – both on the upside and the downside. Most of the time, such shocks are received negatively. Therefore, a crash or anti-bubble becomes inevitable intuitively. However, sometimes, it infuses positivism as well, causing a bubble to build in quick time. Investors do herd when the market becomes more volatile and unpredictable. During the extreme price movements (bullish and bearish period), herding gives these investors a sense of security and hope that majority's investment decisions can turn out to be good (Bartels, 1998; Kallinterakis and Ferreira, 2007). The presence of herding behavior negates the validity of the efficient market hypothesis and rational asset pricing model. Some authors argue that herding behavior may destabilize the market, cause inefficiency in prices by moving values away from their fundamentals, and can result in fragility to the financial system (Bikhchandani & Sharma, 2000);(Demirer & Kutan, 2006); (Hott, 2009).

1.2 HERDING BEHAVIOUR WITH SPECIFICATION TO THE STUDY

Herding behaviour is in general study the course of two diverse approaches. The first, which the present study followed, is often called "Market-wide Herding behaviour" Under this approach the study considers the cross-sectional absolute deviation to detect the market-wide herding behaviour. The market-wide herding does not consider individual investor behaviour. Instead, it focused on more market-wide herding which concentrates on the tendencies of the entire market or sample data. If herding behaviour is present market-wide, returns of stocks clustered around the market return is a result where the investors in the market consider information conscious about and avoid their information. An alternative approach to detecting herding behaviour is by considering some special group of investors behaving similar manner i.e. analysing the herding behaviour from an individual perspective in the way of mutual fund selection, analyst recommendation and trader behaviour with professional managers. Detecting herding behaviour in any other manner finally leads to the same market consent. After understanding the two approaches, the market-wide approach is concerned with stock price dispersion quantitatively and the other approach focuses more on what factors determine or influence the herding behaviour. Standard financial theories such as the Capital Asset Pricing Model (CAPM) and the Efficient Market Hypothesis (EMH) indicate that market participants are logical individuals who aim to maximize their wealth personal health, also known as Homo Economicus. But investors and financial analysts were curious about the technology bubble of the late 1990s and early 2000s, the global recession of 2008, and numerous other similar bubbles throughout history, and the answers provided by conventional finance theories were insufficient to quell their curiosity.

As a result, a brand-new discipline called behavioural finance developed, offering explanations for the market's anomalies. It might clarify how elements like psychological and emotional influences shaped investors' decisions and behaviors.

1.3 CAPITAL ASSET PRICING MODEL (CAPM)

CAPM was pioneered by Sharpe (1963-1964) and Lintner (1965) as an extension of the Portfolio Theory. It was based on the assumptions on the way investment decisions were made by investors. According to CAPM, no matter how much a portfolio is diversified, it will always face some amount of risk. Investors want to earn a return which compensates the amount of risk they take. The CAPM helps to determine and calculate the risk an investment has and the return that comes along. According to William Sharpe who later became a Nobel laureate in economics, an investment bears two types of risks, Systematic risk and Unsystematic risk: ¬ Systematic Risk: These are those risks which cannot be offset by diversification. In other words they those risks which are not in the control of investors to be mitigated example: recession, wars, interest rates etc.. these are market risks which are not in the control of corporate or individual investors ¬ Unsystematic Risk: These are company specific risks and are related to individual securities. These can be mitigated by diversifying the portfolio. For example: A shift in company management, a product recall or a new competitor entering the market According to Sharpe (1963), diversification can help mitigate the unsystematic risk but it can never solve the problem of systematic risk. So while calculating the expected return it is the systematic risk that plagues investors. So CAPM helps to calculate the risk and return associated with an investment

1.4 EFFICIENT MARKET HYPOTHESIS

The Efficient Market Hypothesis (EMH) says that investors can't beat the market and earn higher or above-average returns because share prices will always reflect all available information. Behavioural finance economists have always criticised this theory because they have always believed in market inefficiencies. This theory was developed in the 1960s in the Ph.D. dissertation of economist Eugene Fama who said that securities at any given point in time will reflect their fair values since all information available in the market is reflected in the prices of the stocks. So, they can never be overpriced or underpriced. Fama said that it is impossible to beat the market and earn higher or abnormal returns and if such an event happens, it will be merely by chance or good luck and not because of making some strategies of selecting the right stocks. According to EMH, the market is always right and efficient and investors may not act rationally every time but they can act randomly. ‘Efficient’ here means ‘Normal’. So if investors give an unusual reaction to unusual information then it is considered normal and also random which might not be rational.

1.5 BEHAVIOURAL FINANCE

Theoretical and empirical research provided significant evidence that rational asset pricing models, the efficient market hypothesis and other standard finance theories did a decent work of predicting and explaining certain events to determine the expected value of assets. However, as time passed researchers in both finance and economics started to explore the anomalies and behavioural biases which were not examined in standard finance theories available over the period. While these theories provide some idealised events, the real world proved to be a very confusing place in which investors behaved unpredictably. Behavioural finance is a value-added concept in financial literature; it seeks to supplement the traditional theories of finance by introducing behavioural aspects to the investor’s decision-making process. Opposing standard finance theories, behavioural finance theories deal with the investors’ decision-making process. It analyses the ways that market participants make investment decisions and how the investment decisions of market participants are influenced by different heuristics and emotional biases during the process. Traditional theories assume that investors are rational, while behavioural finance theory argues with the assumption that, investors are irrational. However, a new school of behavioural finance theory believe that, while the traditional financial theory may hold in the long run, in the short run markets are not efficient and investors do not make rational decisions. Investors have a mind and heart but investors do not always make decisions only out of their mind. When decisions are made from the heart those are emotional decisions and may not be rational. It was evidence that most of the losses suffered by the investor were due to their emotional indiscipline and unwillingness to delay gratification. Stock markets offer good investment opportunities in the form of listed companies that are prone to sway between business cycles and sessions of human emotions. But over the long run, investors can benefit from regular dividends and capital appreciation if the choice of the company and its investment model is good. The principle of behavioural finance is how real people make decisions and those make people different which was ignored by the traditional finance theories.

1.6 THE STOCK MARKET INDEX

Stock market indexes serve as vital barometers of the overall health and performance of financial markets, providing investors, analysts, and policymakers with a snapshot of market conditions. These indices aggregate the values of a select group of stocks, representing various sectors or the entire market, and serve as benchmarks for assessing market movements. Examples include the BSE Sensex and Nifty 50 in the Indian stock market. The calculation methods, often based on market capitalization or price-weighted averages, offer insights into the relative performance of constituent companies. Investors use these indices to gauge market trends, make investment decisions, and measure the effectiveness of their portfolios against the broader market. Additionally, stock market indexes play a crucial role in financial research, enabling academics and analysts to study market dynamics, evaluate economic indicators, and understand the impact of various factors on overall market performance.

1.7 NATIONAL STOCK EXCHANGE (NSE)

NSE was the first stock exchange in India which offered an electronic trading mechanism. It was established in 1992. It was in 1995 that the National Securities Depository Limited (NSDL) was established to provide investors with depository services. With the electronic trading mechanism being introduced by the NSE, it became very easy for investors to buy and sell as much as one share. The most popular index of NSE is Nifty 50 where shares of 50 companies are traded. Apart from these two major stock exchanges, the others are the Calcutta Stock Exchange (CSE), Metropolitan Stock Exchange (MSE), India International Exchange (India INX), and NSE IFSC Ltd5. As of May 2021, the total market capitalization of the National Stock Exchange is more than US$3.26 trillion which makes it the world's 7th-largest stock exchange.

NSE Indices Limited (formerly known as India Index Services & Products Limited), or NSE Indices, owns and manages a portfolio of over 350 indices under the NIFTY brand as of August 31, 2023, including NIFTY 50. NIFTY indices are used as benchmarks for products traded on NSE. NIFTY indices served as the benchmark index for 129 ETFs listed in India and 12 ETFs listed abroad as of August 31, 2023. Derivatives benchmarked to NIFTY indices are also available for trading on NSE and NSE International Exchange IFSC Limited (NSE IX) as of August 31, 2023. In the course of this dissertation, the Nifty 50, Nifty Midcap 50, and Nifty Smallcap 50 indices are employed as foundational benchmarks for the comprehensive examination of the Indian stock market. These indices, managed by the National Stock Exchange of India (NSE), are meticulously curated collections of stocks that collectively offer a nuanced representation of diverse market segments. The Nifty 50, consisting of the top 50 companies by market capitalization, serves as a proxy for the broader market performance, while the Nifty Midcap 50 and Nifty Smallcap 50 indices afford insights into the dynamics of mid-sized and small-sized companies, respectively. Furthermore, the study delves into sector-specific indices, including Nifty Auto, Nifty IT, Nifty Financial Services, Nifty Energy, and Nifty FMCG. These sectoral indices facilitate a granular analysis of industry-specific trends and dynamics,

1.8 BROAD INDICES

- **NIFTY 50**

The Nifty 50 is a diversified 50 stock index accounting for 13 sectors of the economy. It is used for a variety of purposes such as benchmarking fund portfolios, index-based derivatives and index funds. Nifty 50 is owned and managed by NSE Indices Limited (formerly known as India Index Services & Products Limited) (NSE Indices). NSE Indices is India's specialized company focused upon the index as a core product.

Market Representation:

- The Nifty 50 Index represents about 59% of the free float market capitalization of the stocks listed on the NSE as of September 29, 2023.
- The total traded value of Nifty 50 index constituents for the last six months ending September 2023 is approximately 34.6% of the traded value of all stocks on the NSE.
- The impact cost of the Nifty 50 for a portfolio size of Rs.50 lakhs is 0.02% for September 2023.

- Nifty 50 is ideal for derivatives trading.

➢ NIFTY MIDCAP 50

The primary objective of the Nifty Midcap 50 Index is to capture the movement of the midcap segment of the market. Nifty Midcap 50 includes the top 50 companies based on full market capitalization from Nifty Midcap 150 index with preference given to those stocks on which derivative contracts are available on National Stock Exchange (NSE).

Market Representation:

- The Nifty Midcap 50 Index represents about 7% of the free float market capitalization of the stocks listed on the NSE as of September 29, 2023.
- The total traded value for the last six months ending September 2023, of all index constituents is approximately 9.6% of the traded value of all stocks on NSE.

The Nifty Midcap 50 Index was computed using the market capitalization-weighted method from the launch date till February 25, 2010.

➢ NIFTY SMALLCAP 50

The primary objective of the Nifty Small cap 50 Index is to capture the movement of the small-cap segment of the market. The index represents the top 50 companies selected based on average daily turnover from the top 100 companies selected based on full market capitalization in the Nifty Small cap 250 index.

Market Representation

- The Nifty Small cap 50 Index represents about 3% of the free float market capitalization of the stocks listed on the NSE as of September 29, 2023.

- The total traded value for the last six months ending September 2023, of all index constituents is approximately 5.3% of the traded value of all stocks on NSE.

1.9 SECTORAL INDICES

- **NIFTY AUTO**

The Nifty Auto Index is designed to reflect the behaviour and performance of the Indian automobile sector. The Nifty Auto Index is computed using the free float market capitalization method with a base date of January 1, 2004, indexed to a base value of 1000.

- **NIFTY ENERGY**

"NIFTY Energy" typically refers to the energy sector index on the National Stock Exchange of India (NSE). The NIFTY Energy index represents the performance of the energy sector stocks listed on the NSE.

- **NIFTY FMCG**

The Nifty FMCG Index is designed to reflect the behavior of FMCG Indian companies from (the moving Consumer Goods) (FMCG) sector. It includes companies that deal with those goods and products, which are non-durable, mass consumption products and available off the shelf.

- **NIFTY IT**

Information Technology (IT) industry has played a major role in the Indian economy. To have a good benchmark for the Indian IT sector, the Nifty IT sector index has been developed. Nifty IT provides investors and market intermediaries with an appropriate benchmark that captures the performance

- **NIFTY FINANCIAL SERVICES**

The Nifty Financial Services Index is designed to reflect the behavior and performance of the Indian financial market which includes banks, financial institutions, housing finance, insurance companies and other financial services

1.10 RESEARCH QUESTIONS

- **RQ1** Does Herding behavior exist in the Indian stock market considering selective broad indices of NSE?
  - **RQ1.1** Does Herding behavior exist in the Indian stock market considering NIFTY 50?
  - **RQ1.2** Does Herding behavior exist in the Indian stock market considering NIFTY Midcap 50?
  - **RQ1.3** Does Herding behavior exist in the Indian stock market considering NIFTY Small Cap 50?

- **RQ2** Does Herding Behavior exist in different sectors of the Indian stock market considering selective sectoral indices of the NSE?
  - **RQ2.1** Does Herding Behavior exist in different sectors of the Indian stock market considering NIFTY Auto?
  - **RQ2.2** Does Herding Behavior exist in different sectors of the Indian stock market considering NIFTY Energy?
  - **RQ2.3** Does Herding Behavior exist in different sectors of the Indian stock market considering NIFTY FMCG?

- **RQ2.4** Does Herding Behavior exist in different sectors of the Indian stock market considering NIFTY IT?
- **RQ2.5** Does Herding Behavior exist in different sectors of the Indian stock market considering NIFTY Financial services?

1.11 AIM AND OBJECTIVES

- **OB 1** To detect the herding behavior in selective broad indices of NSE
- **OB1.1** To detect herding behavior in Nifty 50
- **OB1.2** To detect herding behavior in Nifty Midcap 50
- **OB1.3** To detect herding behavior in Nifty Small cap 50

- **OB 2** To detect the herding behavior in selective sectoral indices of NSE
- **OB 2.1** To detect herding behavior in NIFTY Auto
- **OB 2.2** To detect herding behavior in NIFTY Energy
- **OB 2.3** To detect herding behavior in NIFTY FMCG
- **OB 2.4** To detect herding behavior in NIFTY IT
- **OB 2.5** To detect herding behavior in NIFTY Financial services

1.12 HYPOTHESES

- **Hypothesis 1: There is no evidence of herding behavior among investors in selective broad indices**

- **Hypothesis 1a:** There is no evidence of herding behavior among investors in the Nifty 50 index.
- **Hypothesis 1b:** There is no evidence of herding behavior among investors in the Nifty Midcap 50 index.
- **Hypothesis 1c:** There is no evidence of herding behavior among investors in the Nifty Small Cap 50 index.

➢ **Hypothesis 2: There is no evidence of herding behavior among investors in selective sectoral indices**

- **Hypothesis 2a:** There is no evidence of herding behavior among investors in the Nifty Auto index.
- **Hypothesis 2b:** There is no evidence of herding behavior among investors in the Nifty Energy index.
- **Hypothesis 2c:** There is no evidence of herding behavior among investors in the Nifty IT index.
- **Hypothesis 2d:** There is no evidence of herding behavior among investors in the Nifty FMCG index.
- **Hypothesis 2e:** There is no evidence of herding behavior among investors in the Nifty Financial Services Index.

1.13 RESEARCH GAP

The current study aims to fill the void in the literature by conducting a study that systematically examines and contrasts herding behavior across the Nifty 50, Nifty Midcap 50, and Nifty Small-cap 50 indices. This research also examines Nifty Auto, Nifty Energy, Nifty FMCG, Nifty IT, Nifty Financial Services, this research will contribute significantly to the field by shedding light on the nuances and differences in herding behavior across diverse market segments and across different sectors of the market, thereby enhancing our understanding of investor behavior and market dynamics.

1.14 SCOPE

In this dissertation, we have examined particular sectoral indices and broader indices. Future studies could explore various indices and also incorporate thematic indices into their research. While our study concentrates on the Indian stock market, researchers can explore stock markets from different countries. Additionally, this dissertation specifically addresses the NSE (National Stock Exchange), but future studies could encompass multiple stock exchanges within India and internationally.

CHAPTER 2: LITERATURE REVIEW

2. INTRODUCTION

The present chapter will cover all the important studies done on herding by investors in the stock market. The studies include both foreign and Indian works. The review has been divided into three sections based on the objectives of the study. Section 1 will include studies on Herding behavior which is done in foreign countries. Section 2 will include studies based on the presence of herd behavior among Broad sectors of the Indian stock market. Section 3 will include studies based on the presence of herd behavior among Sectoral sectors of the Indian stock market

2.1 LITERATURE REVIEW

2.1.1 Herding Behavior Overall

Studying human behaviour has long been a goal in many disciplines, such as psychology and economics. In particular, herding behaviour is a phenomenon that has attracted much interest. It refers to people's propensity to act in sync with others instead of forming their conclusions through independent research or analysis. Herding behaviour in the context of financial markets can result in inefficiencies and even financial disasters. This literature review examines herding behaviour and its implications, consequences, and causes.(Chiang & Zheng, 2010) investigated herding behavior in international markets by using daily data from 18 different countries The evidence of herding in Asian and advanced stock markets (apart from the US). Latin American markets show no signs of herding. Herding occurs in both up and down markets, except the US and Latin American markets; nevertheless, during periods of market expansion, herding asymmetry is more pronounced in Asian markets. (Poshakwale & Mandal, 2014). Moreover (Hasan et al., 2023) for the majority of countries, revealed strong evidence of herding in the event of negative tail market conditions, which are driven by non-fundamental information. This study looks at the connection between herding and systemic risk as well, and it finds that as systemic risk rises, herding motivated by fundamentals grows more than herding driven by non-fundamentals. Furthermore, (Ferreruela & Mallor, 2021) conducted a study to know how investors imitated at particularly volatile times, such as the 2008 financial crisis and the most recent worldwide pandemic, which both had the potential to influence investors' feelings and actions. broken down into many sub-periods categorized as well as before, during, and following 2008, COVID-19, and post-Covid-19 crises. The findings demonstrate the existence of herding effects in both markets, but there are variations in the subsamples examined and the market dynamics .(Christie & Huang, 1995) examines the concept of herd behavior in equity returns during market stress. The authors compare the predictions of herd behavior with those of rational asset pricing models when analyzing individual returns during periods of market stress. They use dispersion, which measures the average proximity of individual returns to the mean, to investigate the presence of herding behavior in the market. The empirical studies on herding behavior in financial markets capture various dimensions of investor behavior and its implications for market dynamics. Researchers, such as (Koch & Koch, 2016) have delved into this area, examining sophisticated investors trading on similar signals, agency problems, and irrationality that can influence financial markets. The existing literature provides valuable insights into how investor imitation during periods of uncertainty or significant market changes can lead to correlated behavior patterns, contributing to heightened market volatility. (Mobarek et al., 2014) reveals significant insights into the dynamics of market behavior during periods of crisis. The analysis indicates that herding effects are most pronounced during extreme market conditions, especially in the context of financial crises such as the Global Financial Crisis (GFC) and the Eurozone Crisis (EZC).(Xie et al., 2015) presents innovative findings that significantly advance the understanding of herding behavior in the Chinese stock market. By introducing the WCSV model based on the Arbitrage Pricing Theory (APT), the study overcomes the limitations of existing herding-measuring models, offering enhanced accuracy and reliability in detecting herding patterns. The empirical results covering the years 2006 to 2013 demonstrate the superior fitting and robustness of the WCSV model compared to previous methods. By focusing on time points with extremely significant herding rather than just testing for the existence of herding, the study provides a unique perspective on market rationality, especially in emerging markets like China. (Alexakis et al., 2023) reveal significant insights into the dynamics of herding behavior in response to the COVID-19 pandemic. According to the empirical evidence presented in the study, herding behavior was predominantly observed during the COVID-19 sub-period, indicating a tendency for individuals to mimic each other's investment decisions in the face of perceived risks, much like animals reacting to a predator. The research also indicates that herding was particularly prominent on days with elevated numbers of new COVID-19 cases compared to the previous 7-day moving average. (Munkh-Ulzii et al., 2018) The empirical evidence showcases significant herding across both emerging and frontier markets, highlighting the influence of market conditions and investor behavior. Furthermore, the research underscores that herding tendencies are more pronounced in up markets compared to down markets, and are particularly heightened during low trading volume states.(Corredor & Ferreruela, 2010) The study reveals intentional herding behavior, particularly in heavily traded stocks, using both intraday and daily data analysis methods. The research emphasizes the importance of heavily traded stocks in studying mimetic behavior and highlights the significance of intraday data for uncovering herding effects. Results suggest that the Spanish market, especially in heavily traded stocks, exhibits a tendency towards imitation, indicating a pattern of mimetic behavior among investors.(Blasco et al., 2012) shed light on the intricate relationship between herding behavior and market volatility. The study meticulously examines the impact of herding intensity on various volatility measures, emphasizing the role of intraday data in detecting investor behavior. Through the exploration of herding intensity using the Patterson and Sharma measure, the study uncovers a direct linear influence of herding on market volatility across different volatility metrics. Notably, the results suggest that herding variables can be valuable in forecasting volatility, thus enhancing decision-making processes in the realm of asset pricing, risk management, and derivatives valuation. (Demirer & Kutan, 2006) reveal that herd formation does not exist in Chinese stock markets, as evidenced by statistically significant and positive estimates for specific variables indicating rational asset pricing models are supported. Despite prior studies suggesting herd behavior during market stress, the results indicate that traders in the Shanghai and Shenzhen markets make rational investment choices. Based on the empirical findings presented by (Batmunkh et al., 2020) it is evident that herding behavior is prevalent in the Mongolian stock market . The study examined herding behavior during different market conditions, including bull and bear market periods, and high and low volatility states of markets. The results consistently showed the presence of herding behavior across various scenarios, indicating that investors in the Mongolian stock market tend to collectively follow the actions of others, disregarding their private signals or prevailing market fundamentals. (Chiang et al., 2010) Based on the analysis of herd behavior in the US and South Korean markets, it is evident that herding towards the market portfolio shows significant movements and persistence independently of market conditions, such as return volatility and mean return levels. The study reveals that macroeconomic factors do not effectively explain herding patterns, indicating that market sentiment plays a crucial role in influencing investor behavior. The findings also demonstrate the significant impact of herding towards size and value factors, indicating the complexity of investor behaviors across different market environments. Despite some common patterns in herding between the US and South Korean markets, co-movements are far from perfect, emphasizing that market sentiment may not always transfer internationally. (Vo & Phan, 2017) Through the utilization of the herding measures proposed by Christie and Huang (1995) and Chang et al. (2000), the research indicates the presence of herding behavior among investors in the Vietnam equity market during the study period. The results suggest that herding was more pronounced in downturn markets compared to up markets, showcasing a "flight to safety" tendency among investors during challenging times. (Galariotis et al., 2016) Based on the meticulous investigation into the herding phenomenon and market liquidity in the Vietnam stock market, the study portrays significant evidence of herd behavior existence alongside various market liquidity conditions. The empirical results not only reaffirm the presence of herding across different market states but also shed light on the interconnectedness between return dispersion and market liquidity. (Liu et al., 2023) Market herding behavior is more positively correlated with the least-informed investors' group during the post-peak period, indicating a stronger herding tendency among individual investors compared to institutional investors. In-group herding tendencies influence both fundamental and non-fundamental herding, with informed investors herding more on fundamental factors and uninformed investors herding more on non-fundamental factors. Most-informed investors generally exhibit less herding behavior than least-informed investors in the Chinese stock market, but this gap narrows down during market collapses and periods of uncertainty. The study confirms that least-informed investor herding has a slightly greater impact on market volatility than most-informed investor herding, although both contribute to raising market volatility. (Shrotryia & Kalra, 2022) The study's findings underscore the intricate dynamics of mimicking behavior in both normal and asymmetric scenarios, shedding light on the contagion between the US and BRICS stock markets. Moreover, the examination of herd activity during crises, such as the oil crisis of 2014 and the Chinese crisis of 2015, offers valuable insights into investor behavior under turbulent conditions. These empirical results, showcasing the interplay between various market conditions and herd tendencies, provide nuanced perspectives on the financial landscape within the BRICS nations. The implications extend beyond theoretical discourse, offering practical insights for regulators and money managers in navigating the complexities of stock market behavior during tumultuous times. The study's delineation of herd activity in response to the formation of the New Development Bank highlights the multifaceted influences shaping market dynamics within the BRICS bloc. (Lam & Qiao, 2015) revealed that herding occurs in both market and industrial levels, with variations observed in different market conditions and sub-periods. Industrial herding persisted even when market and size herding disappeared after the introduction of short selling and stock options. The results suggest that investors do not herd on systematic factors when market or industrial herding occurs. Moreover (Bekiros et al., 2017) presents compelling insights into the dynamics of investor behavior in US markets, particularly during uncertain and extreme conditions. The research findings highlight the presence of herding behavior as an inherent characteristic of imperfectly rational traders, driven by emotions and contagion of beliefs The analysis also reveals that herding tends to be stronger in extreme quantiles, with implications for market stability and the potential formation of bubbles. Additionally, the study showcases the evolution of herding patterns across different sub-periods, shedding light on how investor behavior adapts to changing market conditions. (Guney et al., 2017) revealed significant evidence of herding in all eight sample markets between January 2002 and July 2015. The findings indicated that herding was influenced by factors such as market volatility, size-effect, and the return dynamics of key markets like the US and South Africa. Despite observing herding asymmetry during different market conditions, the study showed that market performance did not strongly determine herding behavior in the sample markets. Additionally, the study demonstrated that herding was more pronounced during days of low volatility and that the return dynamics of regional economic initiatives and key stock exchanges affected herding behavior to a limited extent. (Arjoon et al., 2020) revealed that herding is pronounced at both the aggregate market level and in different size-based portfolios. The research indicated that herding behavior can be both spurious and intentional in the overall market and larger portfolios, but only intentional in the smaller portfolios. The analysis also highlighted significant evidence of cross-portfolio herding. Additionally, the results showed that herding tends to be more prevalent during rising market conditions. Lagged microstructures such as liquidity and volatility were found to exacerbate herding at both the aggregate level and in each size-portfolio. The study also considered the time-varying nature of herding by utilizing a state-space model, demonstrating how herding behavior evolves over time in response to market events, microstructures, and investor sentiment. (Alhaj-Yaseen & Yau, 2018) presents insightful findings regarding herding behavior in China's A- and B-markets, particularly before and after market liberalization. The research sheds light on the impact of information heterogeneity on investor herding tendencies. The comparison between individual and institutional investors unveils intriguing trends, with sophisticated institutional investors playing a crucial role in mitigating herding behavior. The findings underscore the importance of the information environment in influencing herding propensities, with investors more likely to herd when information is lacking. The study also points out that when investors are better informed, as seen in the case of sophisticated institutional investors in the B-market, herding tendencies decline. Furthermore (Dang & Lin, 2016) The research documented stronger herding on up market days compared to down market days and confirmed the robustness of herding behavior even when subjected to daily price limit tests. Additionally, there was a significant reduction in the magnitude of herding following the global financial crisis, indicating the impact of market events on investor behavior. By modifying tests for fundamental and non-fundamental herding, the study identified robust evidence of non-fundamental herding when factoring out spurious herding. This insight contributes to the understanding of herd behavior in Vietnam and sheds light on interactions among idiosyncratic investors with heterogeneous information. (Jiang et al., 2022) The study delves into the phenomenon of herding behavior during the COVID-19 period, analyzing six key Asian markets along with international comparisons. The empirical results reveal a clear presence of herding behavior across the Asian markets, particularly during the turbulent period of the market crash in March 2020. Herding was detected in various market states, with an emphasis on the relationship between idiosyncratic volatility and the magnitude of herding. The study showcases a shift in investor sentiment, influenced by the uncertainties surrounding COVID-19 and the ensuing economic repercussions. Furthermore, (Humayun Kabir & Shakur, 2018) delves into the key insights derived from analyzing herding behavior in these markets. The study utilized the smooth transition regression (STR) approach to investigate nonlinearity with regime switches and examined how investors' herding behavior evolves across different market states and volatility regimes. The findings revealed interesting patterns of herding behavior, with some markets tending to herd with market consensus in high market regimes, while others did not exhibit nonlinearity across market states. Investors in most markets, except for Argentina and Brazil, were found to herd in high volatility regimes, highlighting the impact of volatility on herding behavior. (Ah Mand & Sifat, 2021) reveals a multifaceted understanding of market dynamics. The investigation, spanning from 1995 to 2016, delves into the nuances of herding behavior using static and dynamic models, showcasing inconsistent results from classical approaches and the superior explanatory power of a dynamic Markov-Switching model. The research underscores the regime-dependent and non-linear nature of herding, shedding light on the influence of market regimes on investors' behavior. Despite a lack of broad-market herding support in Malaysia, evidence of substantial non-linearities and increased herding during high volatility periods emerged from the dynamic modeling approach. (Economou et al., 2016) revealed significant findings. Herding behavior was observed under different market states, with a higher prevalence in smaller capitalization stocks. The study utilized a survivor bias-free dataset covering the period from 2007 to May 2015 and applied the cross-sectional dispersion approach. The empirical results showed herding effects in the high quantiles of cross-sectional return dispersion and indicated the impact of size effect on herding estimations (Finance Research Letters, 2016). (Balcilar et al., 2014) By examining the influence of own market volatility and global factors on herding behavior in the GCC stock markets, the research sheds light on the drivers behind transitions between non-herding and herding states. Key findings indicate that market volatility plays a significant role in triggering herding behavior, particularly during high volatility and extreme market movements. The study also underscores the impact of global factors, such as the U.S. stock market performance, oil prices, US interest rates, and risk indexes, in contributing to investor herding in the GCC markets. Notable studies contributing to this empirical analysis of herding behavior include the works of (Grinblatt et al., 1995) , (Chang et al., 2000), (Hwang & Salmon, 2004), (Blasco et al., 2009), (M. Cipriani & Guarino, 2009) ,(Blasco et al., 2012), (Tsionas et al., 2022),(B. M. Cipriani & Guarino, 2014), (Schmitt et al., 2017). These studies collectively provide a comprehensive view of how herding behavior influences investor decision-making, market stability, and price dynamics across different financial markets. The empirical analyses shed light on the complex interplay of factors driving herding behavior and its impact on market efficiency and asset pricing

2.1.2 Herding behavior in selective broad indices in India

The studies on herding behavior in the financial markets, particularly focusing on the Indian stock market, indicate a dynamic landscape with varying intensities and patterns of herding across different phases and market conditions. The research reveals a notable presence of herding behavior among market participants, particularly highlighted during specific years of economic turmoil and market volatility. The empirical observations shed light on the intricacies of herding patterns in response to different shocks and events affecting the Indian stock market. The findings underscore the nuanced nature of herding behavior, showcasing its prevalence in specific years characterized by global financial crises, economic downturns, and geopolitical tensions. The identification of consistent bubbles and herding post the Global Financial Crisis, as well as during turbulent market phases like the Covid-19 pandemic, highlights the impact of external shocks on investor behavior and market dynamics. Moreover, the differentiation between small and large stocks further emphasizes the influence of company size on herding tendencies, with small-cap stocks exhibiting more pronounced herding behavior in times of market distress.

Indian investors engaged in herding behavior Negative herding behavior was discovered in the study, highlighting that people are deviating from the market consensus. The subperiod analysis supports the herding behavior that is detrimental. The results remained for large, mid, and small-cap companies alike, except for one year, 2009, for small enterprises (Ansari & Ansari, 2021). Moreover (Kanojia et al., 2022) attempts to analyze the market-wide herding in the Indian stock market during normal market conditions, extreme market conditions, and both increasing and decreasing market conditions. The study studied and tested evidence of herding behavior in the Indian stock market. According to Christie and Huang's (1995) and Chang et al. (2000) studies, which suggested techniques for identifying market-wide herding using stock return data, The findings show no evidence of herding in any market condition. The herding trend in up-and-down markets and extremely volatile stock market situations. The study goes on to disprove any evidence of herding in both bull and bear markets, as well as in extremely volatile markets (Kumar et al., 2018). This study (Satish & Padmasree, 2018) intends to investigate herding behavior in the Indian stock market. The impact of the global financial crisis on herding behavior is another main objective of the study. The study's findings supported the existence of rational asset pricing models by showing that herding behavior has not been seen in the Indian stock market in a long time. India has a sizable working population, a sizable landmass, rising market demand, and supportive government policies. In spite of this, compared to other developing nations, the share of foreign portfolio investments is lower. Due to its unusually high levels of market volatility and pervasive cultural variety, which encourages people to follow one another, the Indian stock market has long faced criticism (Kaur, 2004). Consequently, rather of sticking to their own opinion, investors would rather follow the advice of other people they consider to be knowledgeable investors. (Lao & Singh, 2011) had conducted a study that examines herding behavior in Chinese and Indian stock markets. The results indicate that there is herding behavior in the stock markets of China and India and that this behavior is more pronounced in times of severe market situations. Herding behavior is more pronounced in the Chinese market during market declines and large trading volumes; in contrast, the it happens during market upswings in India. investigated if herd mentality exists in the developing Indian stock market. They discovered that the Herding exhibits notable oscillations and tenacity in both bull and bear markets and that it appears to intensify during the latter . (Saumitra & Sidharth, 2012) Instead of using the conventional portfolio-based approach's standard deviation to test herding behaviour in the Indian equity market, the paper proposes an alternative method that makes use of the symmetric properties of the cross-sectional return distribution. We discover evidence of herding in the Indian market during the sample period using the suggested methodology. We also note significant herding in the Indian equity market during the 2007 crash. In conclusion, we also note that, in contrast to the directional asymmetry reported by McQueen, Pinegar, and Thorley (1996), the rate of increase in security return dispersion as a function of the aggregate market return is lower in days of an up market compared to days of a down market. (Khan & Suresh, 2022) Based on the empirical observation of the Indian stock market, the study successfully identified the presence of shock-induced herding and nascent bubbles across various years, with significant findings in 2012 and the years following the Financial Crisis and the Pandemic. The Hurst exponent analysis revealed high levels of herding and bubble during times of crisis and uncertainty, aligning with previous research on economic shocks and market behavior. These insights shed light on the interconnectedness of external shocks and investor behavior, emphasizing the prevalence of herding and bubble formation during tumultuous period (Bikhchandani & Sharma, 2000) emphasizes the prevalence of herding behavior among investors, particularly in emerging markets such as Korea. The authors shed light on the impact of herding on market dynamics, showing how foreign investors utilized positive-feedback trading strategies in the pre-crisis period. Additionally, the study reveals differences in herding intensity based on investor types and trading instruments, highlighting the complex nature of herd behavior in financial markets.(Chauhan et al., 2020) In examining large-cap and small-cap stocks over a period from 2011 to 2015, the research reveals that herding behavior is more pronounced in large-cap stocks compared to small-cap ones, with the former exhibiting a nonlinear relationship between market return and stock dispersion. This suggests that investors tend to herd towards the market index in large-cap stocks, influencing price dynamics and risk factors. (Shah et al., 2017) has provided valuable insights into various facets of investor behavior and market dynamics. The analysis revealed that individual firms do not exhibit herding behavior towards the market index, except during extreme downturns. Moreover, large firms demonstrated herding tendencies in extreme market movements, highlighting the influence of firm size on investor behavior. The study also found evidence of firms herding towards industry portfolios, particularly in upward market swings. However, there was weak evidence of industry portfolios herding towards the market, suggesting a complex interplay between individual firm behavior and industry dynamics.(Choudhary et al., 2022) presents compelling evidence that market return plays a pivotal role in influencing herding behavior, emphasizing a bidirectional relationship. The empirical results indicate that during volatile market conditions, FIIs tend to refrain from herding. This study sheds light on the dynamics of FIIs' investment behavior and its impact on stock market returns, trading volume, and volatility from 1999 to 2017. The findings underline the importance of understanding herding tendencies among FIIs and their implications for market efficiency and investor decision-making. In conclusion, this research provides valuable insights for investors, regulators, and policymakers in navigating the complexities of the Indian equity market and optimizing investment strategies for sustainable growth.

2.1.3 Herding behavior in selective sectoral indices in India.

Since herding behaviour in the Indian stock market has implications for investor decision-making and market efficiency, research has historically gained traction. The frequency of herding in different sectors and its effects on stock prices and market stability have been the subject of numerous studies.(Krishna & Suresha, 2021) conducted a study to find evidence of herding and bubbles contained in the Indian stock indices of the CNX Nifty 50 and CNX Nifty 100 (both in the area of high-frequency trading) amid the events of escalating geopolitical tensions between India Pakistan and China. To capture the effect of these events on herding behavior and information uncertainty in the stock indices under consideration, the study used an event window technique. Employing Multifractal Detrended Fluctuation Analysis (MFDFA), The study's primary empirical findings effectively revealed the herding and bubble formation traces buried in the stock indices assessed throughout the event inquiry. Furthermore (Krishna & Suresha, 2022) had carried out research looking at how investors' herding behavior in the sectoral indices of the National Stock Exchange will be affected by the rise of the geopolitical tensions between China and India in 2020. In an increased geopolitical event window, the high-frequency data of three main NIFTY sectors indices (Auto, Energy, and Pharma) are utilized to identify exactly the signs of the investors' herding behavior. (Ganesh et al., 2016) The study on industry herding behavior in the Indian stock market found that overall, there was no significant level of herding observed in any of the industrial sectors examined. However, during certain years and specific quarter periods, there were instances of significant herding in some sectors, which coincided with excellent growth in those sectors. Furthermore (Kumar & Bharti, 2017) delves into examining the presence of herding behavior among investors and market participants in the Indian equity market, specifically focusing on the Information Technology (IT) sector. The conclusion drawn from the study suggests that the Indian IT sector index exhibits an efficient market where investors make rational investment decisions based on individual information rather than engaging in herding behavior. Moreover (Mishra & Mishra, 2023) examined the herding behavior in the banking and financial sectors in the Indian stock market amid the COVID-19 pandemic. Over the entire sample period, it was observed that investors in these sectors did not exhibit herding behavior at any quantile of the return distribution Additionally, during bullish market conditions amid the pandemic, herding behavior was detected at high quantiles (90%) in the public sector banking and financial services sectors. The study by (Cakan & Balagyozyan, 2014) aimed to fill this gap by investigating herding behavior across different industrial sectors in the Borsa Istanbul stock market from 2002 to 2014. Using a methodology proposed by Chang et al. (2000), the researchers found strong evidence of herding behavior across all sectors, even after controlling for market regimes and firm fundamentals. The study identified asymmetric herding patterns, with more prominent herding observed in rising markets, particularly in the financial, services, and technology sectors during periods of high volatility.(Zheng et al., 2017) provides valuable insights into the dynamics of investor behavior within specific industries across various Asian markets. The findings highlight the presence of industry-level herding in Asian stock markets, with technology and financial industries exhibiting stronger herding tendencies compared to utilities. The study also demonstrates that herding activities are more pronounced in down markets, low trading volume markets, and in industries with specific fundamental characteristics such as market value, P/E ratio, and dividend yield. Moreover, the analysis reveals cross-industry herding effects, indicating how herding behavior in one industry can influence and be influenced by other industries.(Litimi et al., 2016) The examination of herding dynamics across various market sectors sheds light on the complexity of investor behavior and market volatility. The findings suggest that herding is a driving force behind market bubbles in certain sectors, highlighting the impact of trading volume and investor sentiment on herd co-movement. The study underscores the importance of understanding the role of herding in shaping market dynamics and the need for effective risk management strategies. By delving into the nuances of sector-specific herding behaviors. Moreover (BenSaïda, 2017) unveiled a significant presence of herding behavior during financial crises and bubbles across various sectors. The research introduced a modified herding model that demonstrated a negative impact of herding on conditional volatility in most sectors, highlighting the intricate relationship between herding behavior and market dynamics. The empirical investigation not only sheds light on the association between herding and volatility but also emphasizes the sectorial context's importance when studying market behavior. (Medhioub & Chaffai, 2019) Based on the sectoral analysis conducted for the Islamic GCC stock market, the research revealed significant evidence of herding behavior among investors in sectors such as banking, insurance, and hotels, restaurants, and foods during falling market periods. This behavior was notably absent during rising market periods. The study also highlighted the influence of conventional market return dispersion on the Islamic sectors, particularly during both falling and rising market periods. The asymmetry between up and down market periods further emphasized the varying impact of herding behavior across different sectors, with herding tendencies observed around conventional sectors during stress market periods. (Cakan, 2016) presents robust evidence of herding behavior across all industrial sectors within the Turkish stock market. The empirical results reveal a significant degree of herding, even after controlling for market conditions and firm fundamentals. Moreover, asymmetries in herding behavior were observed, with stronger herding tendencies in rising markets and high market volatility, particularly evident in the financial, services, and technology sectors. (Jiang et al., 2022) The analysis of different market sectors, including healthcare and tourism & hospitality industries, provides insights into the specific impacts of the pandemic on these sectors. The detection of herding in industry-specific contexts adds a layer of complexity to understanding investor behavior during times of crisis. (Dhall & Singh, 2020) Based on the analysis of industry herding behavior before and after the COVID-19 outbreak in India's stock market, the findings suggest a notable shift in investor behavior. The research reveals a lack of significant evidence of herding behavior in industries before the pandemic, indicating individual decision-making or anti-herding tendencies. However, post-pandemic, there is a notable emergence of herding behavior in specific industries like automobile, IT, and pharmaceuticals, possibly due to changing market dynamics and uncertainties created by the COVID-19 environment.

CHAPTER 3: METHODOLOGY

3. INTRODUCTION

The chapter focuses on the way the research has been conducted. It elaborates on sample selection, sources of data and framework for analysis that have been adopted to ensure the existence of herd behavior in Indian stock

3.1 METHODOLOGY

The data is secondary data, which is collected from the National Stock Exchange (NSE) website, i.e., daily data on broad and sectoral indices prices. The period of study is eight years, i.e. 2016 – 2023. The statistical tools and techniques used are Descriptive statistics, Augmented Dickey-Fuller (ADF), and Phillips-Perron (PP) tests to test the stationarity and Regression model. The study used Cross-sectional absolute deviation (CSAD) to detect the herding activity.

Cross-sectional absolute deviation (CSAD): Cross-sectional absolute deviation (CSAD) was developed by (Chang et al. 2000) (CCK) in 2000. It is a modified method based on CSSD by (Christie and Huang, 1995) CH in 1995. By definition, CSAD takes on a minimum value of zero when all individual stock returns move in perfect unison with the market and increases when the returns of individual stocks deviate from the market returns

Formula

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

Where,

Rit is the daily stock return of firm i at time t

Rmt is the cross-section of the average of N returns in the aggregate market portfolio at time t

N is the number of securities in the sample

3.2 BASIS FOR DETECTING HERDING UNDER CCK MODEL

In the CCK Model equation, a negative b3 value, the coefficient of squared market return shows the presence of positive herding if P value is below 0.05 at 5% level of significance. A positive b3 value, the coefficient of squared market return shows the presence of negative herding if P value is below 0.05 at 5% level of significance.

3.3 STEPS TO DETECT HERDING BEHAVIOR

The study used one metric i.e. CSAD to determine herding behavior. On a broad basis, the following steps were taken to prepare the data for the respective models to be applied.

Step 1. Collect the selected sample daily closing price.

Step 2. Arrange the same in accordance to a particular date

Step 3. Calculate the daily stock returns using the formula **Ri** = $(\mathbf{Pt}/\ \mathbf{Pt{-}1}) * \mathbf{100}$ Where **Ri** stands for stock returns, Pt stands for Current closing stock price, and $\mathbf{Pt{-}1}$ stands for previous day's closing stock price.

Step 4. Calculate the market returns To calculate the market return, the closing market price of Nifty 50, Nifty midcap 50, Nifty small cap 50, Nifty Auto, Nifty Energy, Nifty FMCG, Nifty IT, Nifty Financial Services, was collected on daily basis and calculated in the same way as stock return. **R**m = $(\mathbf{Pt}/\ \mathbf{Pt{-}1}) * \mathbf{100}$ Where **R**m stands for market returns, Pt stands for Current closing market price, and **Pt−1** stands for previous day's closing market price

Step 5. ADF and PP tests were used to determine the series' stationarity characteristics.

Step 6. CCK Model was applied to detect herd behavior in the market.

3.4 CCK MODEL EQUATIONS FOR IDENTIFYING HERDING BEHAVIOR

	EQUATIONS FOR BROAD INDICES
1	$CSAD_{Nifty\ 50} = \alpha + \beta_1\ Rm + \beta_2\ \|Rm\| + \beta_3\ R^2m + \varepsilon$
2	$CSAD_{Nifty\ midcap\ 50} = \alpha + \beta_1\ Rm + \beta_2\ \|Rm\| + \beta_3\ R^2m + \varepsilon$
3	$CSAD_{Nifty\ smallcap\ 50} = \alpha + \beta_1\ Rm + \beta_2\ \|Rm\| + \beta_3\ R^2m + \varepsilon$

	EQUATIONS FOR SECTORAL INDICES
1	$CSAD_{Auto} = \alpha + \beta_1\ Rm + \beta_2\ \|Rm\| + \beta_3\ R^2m + \varepsilon$
2	$CSAD_{Energy} = \alpha + \beta_1\ Rm + \beta_2\ \|Rm\| + \beta_3\ R^2m + \varepsilon$
3	$CSAD_{FMCG} = \alpha + \beta_1\ Rm + \beta_2\ \|Rm\| + \beta_3\ R^2m + \varepsilon$
4	$CSAD_{IT} = \alpha + \beta_1\ Rm + \beta_2\ \|Rm\| + \beta_3\ R^2m + \varepsilon$
5	$CSAD_{Financial\ services} = \alpha + \beta_1\ Rm + \beta_2\ \|Rm\| + \beta_3\ R^2m + \varepsilon$

Here, CSAD is a measure of return dispersion, α is the constant term | Rm | is the absolute return term β_1, β_2 and β_3 are the coefficients of market return, absolute market return and squared market return R^2m captures the nonlinear relationship through a negative estimate of the coefficient b3

CHAPTER 4: ANALYSIS AND CONCLUSION

4. INTRODUCTION

In this chapter, the findings from the empirical analysis of Herding Behavior are systematically examined and interpreted to address the research questions and objectives outlined in Chapter 1 . Through a comprehensive analysis of the gathered data, this chapter aims to uncover patterns, relationships, and insights essential for understanding Herding Behavior in the Indian Stock Market

4.1 DESCRIPTIVE STATISTICS

Descriptive statistics provides a concise summary of data features. It includes measures like mean, median, and mode to represent central tendency, as well as range, variance, and standard deviation for dispersion. Univariate analysis focuses on single variables, while bivariate and multivariate analyze relationships between two or more variables. Presentation methods include tables for organized data and graphs for visual representation. Its applications span various fields, aiding in decision-making and trend identification. Though valuable, it has limitations such as oversimplification and potential misinterpretation. Understanding its concepts and applications is vital for effective data analysis and interpretation (Alabi & Bukola, 2023).

4.1.1 Table 1 Descriptive statistics of Broad Indices

	CSAD	Nifty 50 R_m	CSAD	Nifty mid-cap 50 R_m	CSAD	Nifty small cap 50 R_m
Mean	0.00058	5.97E-05	0.018056	0.000766	0.019595	0.000517
Median	3.23E-05	0.000821	0.015572	0.002147	0.017204	0.002178
Maximum	1.00397	0.087632	0.530369	0.064396	0.132923	0.0607
Minimum	-0.104107	-1	0.00542	-0.148936	0.002672	-0.137541
Std. Dev.	0.025202	0.024921	0.014624	0.013553	0.009567	0.014108
Skewness	31.98881	-32.82111	22.69123	-1.255395	3.538207	-10311392
Kurtosis	1274.392	1315.073	766.6861	13.48618	26.7509	10.68606
Jarque-Bera	1.33E+08	1.42E+08	48260886	9586.941	50644.35	5438.503
Probability	0	0	0	0	0	0
Sum	1.145774	0.117842	35.73278	1.515531	38.77779	1.023514
Sum Sq. Dev	1.253806	1.225982	0.422999	0.363303	0.181038	0.393692
Observations	1975	1975	1975	1975	1975	1975

Source: EViews output compiled by Author

An extensive summary of the performance of the financial market's broad indices is provided by the descriptive data shown in Table 1. The average return for the CSAD Nifty 50 index for the observed time is 0.000580, the mean return. By contrast, the Nifty Mid-cap 50 and Nifty Small-cap 50 indices had far lower mean returns, at 0.000766 and 0.000517, respectively. This implies that different broad indices have performed at different levels. The data distribution's core tendency may be gained by the median values. The highest and minimum returns show the range of performance within each index. For example, the CSAD Nifty 50 index exhibits volatility and the potential for both large profits and losses, with a maximum return of 0.087632 and a minimum return of -1.00000. Similarly, the maximum and lowest returns of the Nifty Mid-cap 50 and Nifty Small-cap 50 indices show different degrees of volatility. A leptokurtic distribution is shown by positive kurtosis, and a platykurtic distribution is shown by negative kurtosis. Long right tails were represented by positive skewness, and long left tails were represented by negative skewness.

4.1.2 Table 2 Descriptive statistics of Sectoral Indices

	CSAD	Nifty IT R_m	CSAD	Nifty Energy R_m	CSAD	Nifty Auto R	CSAD	Nifty FS R_m	CSAD	Nifty FMCG Rm
Mean	15187	0.000675	0.0155	0.000267	0.015699	0.000509	0.016985	0.000152	0.013566	0.00058
Median	0.012668	0.000592	0.012641	0.001116	0.012736	0.000819	0.01376	0.000832	0.011974	0.000488
Maximum	0.112133	0.104386	0.123805	0.086344	0.168469	0.104063	0.145425	0.093197	0.10361	0.083185
Minimum	0.000297	-0.09575	0	-1	0.000644	-0.138478	0	-1	0.000793	-0.105954
Std. Dev.	0.010037	0.013363	0.0108	0.026007	0.012062	0.014259	0.012291	0.026431	0.007698	0.010465
Skewness	3.308273	-0.089316	3.189479	-28.86331	4.741711	-0.265971	4.026894	-27.54567	4.257581	-0.181334
Kurtosis	21.33104	10.48586	20.27903	1109.18	42.29696	13.11264	27.18099	1040.005	33.44304	15.63441
Jarque-Bera	31254.83	4614.1	27932.09	1.01E+08	134479.9	8438.88	53482.4	88789515	82232.98	13146.89
Probability	0	0	0	0	0	0	0	0	0	0
Sum	29.99431	1.333053	30.62865	0.528021	31.0064	1.00599	33.56171	0.300036	26.79365	1.146414
Sum Sq. Dev	0.198856	0.352494	0.230383	1.335805	0.287191	0.401352	0.298337	1.379731	0.116992	0.216173
Observations	1975	1975	1975	1975	1975	1975	1975	1975	1975	1975

Source: EViews output compiled by Author

Table 2 presents descriptive statistics about sectoral indices within the financial market, providing insightful information on the performance traits of specific sectors. The average performance of every sector over the observed time is seen in the mean returns for the sectoral indices. To illustrate the average return for equities in the IT sector, the Nifty IT index displays a mean return of 0.000675. In contrast, the mean returns of the Nifty Energy, Nifty Auto, Nifty Financial Services, and Nifty FMCG indices are 0.000267, 0.000509, 0.000152, and 0.000580. The diverse performance levels in the various industries are reflected in these figures. The central tendency of each sector's return distributions may be inferred from the median returns. The Nifty Auto sector stands out with a median return of 0.000819, representing the middle value of returns for this sector. The Nifty Energy sector, in comparison, has a lower median return of 0.000267, indicating a distinct return distribution within this industry. A comparison of each industry index's maximum and minimum returns reveals the range of possible performance possibilities. Furthermore, examining the skewness and kurtosis data may help understand each sector's return distribution's shape and tail behaviour. Significant skewness and kurtosis readings indicate non-normality and possible departures from a bell-shaped, symmetric distribution within some sectors.

4.2 UNIT ROOT

Augmented Dickey-Fuller test (ADF Test) and **Phillips-Perron test (PP test),** which are the most common statistical tests used to test whether a given Time series is stationary or not. These 2 tests are the most commonly used statistical tests when it comes to analyzing the stationarity of a series. Stationarity is a very important factor in time series. In probability theory and statistics, a **unit root** is a feature of some stochastic processes (such as random walks) that can cause problems in statistical inference involving time series models. A linear stochastic process has a unit root if 1 is a root of the process's characteristic equation. Such a process is non-stationary but does not always have a trend. If the other roots of the characteristic equation lie inside the unit circle—that is, have a modulus (absolute value) less than one—then the first difference of the process will be stationary; otherwise, the process will need to be differenced multiple times to become stationary. If there are d unit roots, the process will have to be differenced d times in order to make it stationary. Due to this characteristic, unit root processes are also called **difference stationary.**

4.2.1 Table 3 Results of Unit root test (ADF & PP)

Stationarity Test	ADF Test				PP Test			
	CSAD		R_m		CSAD		R_m	
	t-stats	p-value	t-stats	p-value	t-stats	p-value	t-stats	p-value
Nifty 50	-18.16	0.0000	-19.20	0.0000	-20.40	0.0000	-19.00	0.0000
Nifty Midcap 50	-7.25	0.0000	-43.37	0.0000	-50.42	0.0001	-43.56	0.0001
Nifty Small cap 50	-5.43	0.0000	-38.48	0.0000	-45.10	0.0001	-39.39	0.0000
Nifty Energy	-7.76	0.0000	-21.72	0.0000	-44.79	0.0001	-21.84	0.0000
Nifty IT	-5.98	0.0000	-45.41	0.0001	-45.59	0.0001	-45.40	0.0001
Nifty Auto	-5.13	0.0000	-43.88	0.0001	-52.76	0.0001	-43.96	0.0001
Nifty FMCG	-6.07	0.0000	-45.83	0.0001	-45.96	0.0001	-45.81	0.0001
Nifty Financial Services	-4.83	0.0000	-22.52	0.0000	-44.17	0.0001	-21.96	0.0000

Source: EViews output compiled by Author

Results of unit root testing are shown in Table 3 for the Nifty 50, Nifty Midcap 50, Nifty Small Cap 50, Nifty Energy, Nifty IT, Nifty Auto, Nifty FMCG, and Nifty Financial Services indices, among other financial market indices. For every index, the statistics for the Phillips-Perron (PP) (Phillips & Perron, 1988) and Augmented Dickey-Fuller (ADF) tests (Dickey & Fuller, 1979) are provided, along with the appropriate p-values. To evaluate the stationarity of the data series, it is frequently necessary to identify if a unit root exists in time series data. The ADF and PP tests are frequently employed to do this. When a time series has a unit root, it is non-stationary, which means that its statistical characteristics, including mean and variance, change with time. Extremely negative t-statistics and accompanying p-values show that the unit root test results show significant findings for all indices. These findings provide compelling evidence that no unit root exists in the indices' return series, suggesting that the data are stationary. The Nifty 50, Nifty Midcap 50, Nifty Small Cap 50, Nifty Energy, Nifty IT, Nifty Auto, Nifty FMCG, and Nifty Financial Services indices, in particular, all show statistically significant p-values [i.e. the p values are less than 0.05] at conventional levels and t-statistics that are much below critical values. This suggests that the return series for these indices are stationary processes without a unit root. Financial time series analysis requires the rejection of the unit root hypothesis to predict and anticipate asset returns with greater accuracy. Stationary data offer more accurate insights into the underlying dynamics of the financial markets and are more straightforward to deal with in econometric models.

4.3 REGRESSION ANALYSIS

Regression analysis is a statistical tool for the investigation of relationships between variables. Usually, the investigator seeks to ascertain the causal effect of one variable upon another—the effect of a price increase upon demand, for example, or the effect of changes in the money supply upon the inflation rate. To explore such issues, the investigator assembles data on the underlying variables of interest and employs regression to estimate the quantitative effect of the causal variables upon the variable that they influence. The investigator also typically assesses the "statistical significance" of the estimated relationships, that is, the degree of confidence that the true relationship is close to the estimated relationship (Humpage, 2000).

4.3.1 Table 4 Results of Regression Analysis (Broad Indices)

	R-square	Coefficient of R_m	Coefficient of Absolute_R_m	Coefficient of Squared_R_m	t-statistics (R^2)	Prob.
Nifty 50	0.916251	-0.792453	-0.040172	0.250937	9.280309	0.0000
Nifty Midcap 50	0.168642	0.044459	0.395458	4.291671	5.501207	0.0000
Nifty Small cap 50	0.319440	0.063823	0.269747	5.374983	10.32392	0.0000

Source: EViews output compiled by Author

By estimating a relationship in which the squared value of market return functions as the independent variable and the cross-sectional absolute deviation (CSAD) as the dependent variable, the analysis performed in Table 4 clarifies findings relevant to herding tendencies. A negative and statistically significant coefficient of the independent variables (with a p-value less than 0.05) suggests substantial herding behaviour. The results show that the squared market return coefficients for the Nifty Smallcap 50, Nifty Midcap 50, and Nifty 50 are 5.374983, 4.291671, and 0.250937, respectively. These coefficients show a statistically significant positive correlation, indicating no strong herd behaviour in the examined market categories. The conclusion from the positive and statistically significant coefficients of the squared market returns is that investors in these market sectors do not show a substantial inclination to herd.

4.3.2 Table 5 Results of Regression Analysis (Sectoral Indices)

Indices	R-square	Coefficient of R_m	Coefficient of Absolute_R_m	Coefficient of Squared_R_m	t-statistics	Prob.
Nifty Energy	0.303853	0.010070	0.692211	-0.689984	-23.38901	0.0000
Nifty IT	0.441515	0.015979	0.404745	5.537355	9.597015	0.0000
Nifty Automobile	0.489289	0.060261	0.387893	6.796892	13.93963	0.0000
Nifty FMCG	0.448545	0.038699	0.351195	6.535968	12.27821	0.0000
Nifty Financial services	0.466727	0.016133	0.858128	-0.849475	-31.47722	0.0000

Source: EViews output compiled by Author

Table 5 analysis provides insights into herding behaviours by estimating a relationship between the cross-sectional absolute deviation (CSAD), the dependent variable, and the squared value of the market return, the independent variable. This approach requires harmful, statistically significant coefficients with a p-value less than 0.05 linked to the independent variables to detect significant herding behaviour. After examining the results, it can be observed that the squared market return coefficients for Nifty IT, Nifty Auto, and Nifty FMCG are positive and statistically significant. This observation implies no significant herd behaviour exists in the corresponding market categories. On the other hand, Nifty Energy and Nifty Financial Services exhibit negative and statistically significant coefficients of squared market returns. These results suggest that herd behaviour exists in these particular market segment

4.4 FINDINGS & CONCLUSION

We investigated the existence and effects of herding behaviour in the Indian stock market in depth in this research, concentrating on sectoral and broad indices that are listed on the National Stock Exchange (NSE). Through rigorous statistical analysis and data evaluation from 2016 to 2023, we hoped to shed light on the intricate dynamics of investor behaviour and its consequences for market performance. We did this by utilising the CSAD technique by (Chang et al., 2000). Our analysis's conclusions offer fascinating new perspectives on how market players behave. Positive and statistically significant coefficients associated with squared market returns support our findings that no substantial herding behaviour exists across broad indices like the Nifty 50, Nifty Midcap 50, and Nifty Small Cap 50. This implies that investors in these categories are likelier to make their own decisions than going with the flow. Additionally, we looked into sectoral indices, including Nifty Energy, Nifty FMCG, Nifty IT, Nifty Financial Services, and Nifty Auto. Here, the results showed a mixed trend. Negative and statistically significant coefficients linked to squared market returns suggested that some sectors demonstrated herd behaviour. In contrast, other sectors showed traits of individual decision-making similar to the broader indices. This implies that investors in these industries are more likely to adopt current market trends, which might increase systemic risk and market volatility. Our work adds to the body of literature already in existence by presenting actual data about the occurrence and significance of herding behaviour in the Indian stock market. Our findings provide important insights for investors, market players, and regulators by defining the subtle differences across different market groups. In an increasingly linked global financial landscape, supporting market efficiency, stability, and resilience requires understanding the causes of investor behaviour.

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