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South Asian Journal of Management Research (SAJMR)

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C O N T E N T S

Herding behaviour in the Indian stock market through Static and Dynamic Approaches: Evidence from the NSE-100

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Abstract

This study investigates herding behaviour in the Indian stock market. The study has collected 2,475 daily, 521 weekly, and 119 monthly closing prices for the Nifty 100 index and its constituent stocks. The data were collected from the Prowess IQ database, managed by the Centre for Monitoring the Indian Economy (CIME), covering the period from 2013 to 2023. This study used the CSAD model developed by Chang et al. (2000), which investigates herding behaviour based on the static and dynamic approaches of the Indian stock market. The static model used Ordinary Least Squares (OLS) regression for analysis. In contrast, the dynamic models utilised Markov regime-switching models, as introduced by Hamilton in 1989. These methodologies were applied to gain insights into the presence and nature of herding behaviour in the Indian stock market during the different regimes. Relying on the static approach, the investor's anti-herding behaviour was evident daily, weekly, and monthly. Moreover, the herding behaviour was found in the dynamic model in the daily dataset, but anti-herding behaviour was apparent in the weekly and monthly datasets. Comparing the results of the static and dynamic approaches, herding prevails during the regime change. From the practitioner's perspective, this study provides valuable insights for investors in the Indian Stock Market and policymakers regarding asset pricing, portfolio diversification, trading strategies and market stability. Many studies explore herding in the Indian stock market, but not specifically through both approaches. This study fills this literature gap by comprehensively examining the herding in the Indian Stock market through Static and Dynamic approaches.

Keywords: Stock Market, Herding Behaviour, CSAD, Markov-Regime Switching Model.

Introduction

Financial market participants have historically believed that investment selections are rational and sensible. It was assumed that reasonable investors would select a portfolio that offered the optimal combination of return and risk. Furthermore, it was believed that financial markets were efficient and could only provide participants with the expected profits. Academic research focused on these idealised assumptions until the global financial crisis, questioning these traditional theoretical principles. As a result, behavioural finance—a field emphasising the importance of behaviour, emotions, personality, and cognition in everyday decision-making—has dramatically changed economic analysis. Today's Researchers claim that there is no single, universal problem-solving approach. Therefore, an academic study must incorporate modern psychological principles to understand investment decision-making's dynamic and ever-evolving process (Suresh, 2024; Sattar et al., 2020). Several biases that taint investment decisions have been exposed by behavioural finance. These presumptions serve as general guidelines for resolving any difficult decision. Shiller (2000) even links these anomalies to the never-ending cycle of economic frictions. Biases include overconfidence, self-attribution, herding, anchoring, representativeness, and mental accounting, which are all captured in the literature on finance. Of all the preferences mentioned earlier, herd activity has been proven to be most disastrous for the stability and functioning of the financial markets (Javaira and Hassan, 2015; Bogdan et al., 2023; Choi & Yoon, 2020). Herd behaviour is frequently blamed for producing deceptive bubbles and inviting noise traders into the stock market to exploit mispricing and push assets from their true intrinsic worth (Kallinterakis et al., 2010; Costa et al., 2024; Mishra & Mishra, 2023; Bouri, 2021).

Numerous authors and researchers have employed the models to detect herding behaviour in various market conditions, including up and down markets, high or low volatility periods, and even during financial crises. Most research articles exploring the CSAD measure of herding have adopted constant coefficient models and utilised the Ordinary Least Squares (OLS) method. Babalos et al. (2015) argued that the parameter is constant in static models, and the conclusion can be misleading. The herding behaviour of the investor is not a continual phenomenon but rather a time-varying one. The study's primary purpose is to address the methodological gap in the Indian context while investigating herding behaviour. Most Indian studies have considered the OLS and the Quantile regression. In this study, the Markov regime-switching regression model was developed by Hamilton

(1989) and is used to capture the herding behaviour of investors in the Indian stock market. The Markov Switching or regime-switching model is instrumental when the underlying data exhibit structural changes over time, where the relationships between variables may vary across different states or regimes. In the Markov regime-switching regression model, the time series data is assumed to be governed by a hidden Markov process, where the system switches between different regimes according to a Markov chain. Each regime is associated with a different set of regression parameters, capturing the distinct relationships between the variables in that regime. The model allows for estimating probabilities associated with each regime, indicating the likelihood of the system being in a particular state at any given time. This will enable researchers to identify periods of stability and instability within the data and to understand how the relationships between variables change during different economic or market conditions.

Furthermore, the Indian stock market, an emerging market, has witnessed volatility in recent years due to global shocks (Vidya et al., 2022), domestic macroeconomic fluctuations, and policy reforms (Kashif et al., 2020), with increasing participation from retail investors and the growing influence of foreign institutional investors. Empirical studies on the Indian context have predicted that herding tendencies during bullish and bearish phases, where investors mimic the actions of others (Choi & Sias, 2009), lead to temporary asset mispricing and deviation from fundamentals (Alamsyah et al., 2023). Events such as the COVID-19 pandemic (Hu et al., 2022; Jabeen et al., 2022) and the Russia-Ukraine conflict (Singh & Debnath, 2024) have further intensified herding behaviour, as investors collectively shifted their positions to minimise perceived risks during market turbulence (Kyriazis, 2020). However, the above studies have been done based on the static approach. Here, the main question arises: Do the changes in regime or state lead to the herding behaviour of the investors in the stock market? To answer this question, the study's primary purpose is to investigate the herding behaviour based on the static and dynamic approaches.

The remainder of the study is organised as follows. The next section provides the literature review based on the previous studies. Section 3 describes the data and methodology. Section 4 analyses the results and discussions, and Section 5 summarises the findings of the study's conclusion.

Review of Literature

It poses a challenge to define herding behaviour in the financial world. It is hard to describe spurious actions and intentional herding in normal market behaviour (Devenow & Welch, 1996; Bogdan et al., 2022; Aharon, 2021). Spurious herding occurs when investors imitate others' decisions without necessarily sharing the same information. In contrast, intentional herding involves investors irrationally copying peers' decisions and disregarding their information. Two primary forms of herding behaviour are identified—rational and irrational. From an illogical point of view, Ahmad (2022), Bogdan et al. (2022), Christie and Huang (1995) characterise herding as individuals suppressing their beliefs and making investment decisions solely based on collective market actions, even if they disagree with the expected outcomes. Chang et al. (2000) describe herding as irrational market behaviour where investors abandon their prior beliefs to follow others unthinkingly. On the rational side, herding occurs when less experienced managers intentionally mimic senior investors, ignoring their private information because they believe others' decisions are more informed. This strategic herding allows them to uphold their reputation in the market (Gurung et al., 2024; Khan et al., 2024; Devenow & Welch, 1996).

Herding, deeply rooted in behavioural finance, has been extensively explored in literature, with its origins attributed to Banerjee's seminal work in 1992. Banerjee's experiment revealed a pattern wherein successive decision-makers relied heavily on the information possessed by their predecessors (Arnott & Gao, 2021). This resulted in a cascading of information, leading individuals to follow the prevailing trend and neglect their signals. This behaviour resulted from widespread conformity driven by observational learning, effectively minimising tangible and financial costs (Welch,1992). However, the detrimental cycle of information spillover is interrupted when there is a reduction in information asymmetry, and the cost of acquiring new strategic data becomes more favourable compared to the associated benefits. This phenomenon is technically termed the fragility of cascades (Bikhchandani et al.,1998)

While detecting herding behaviour, two approaches came forward from the extensive literature review. In the first approach, Lakonishok et al. (1992) conducted pioneering research on herding, investigating the impact of herding and positive feedback trading on stock price destabilisation. The study defined herding as the tendency to imitate the investment actions of fellow fund managers simultaneously, while positive feedback trading involves buying winning stocks and selling losing ones. The study also developed a model to assess herding by analysing a subset of market participants over time. Surprisingly, the study found no significant evidence of herding or positive feedback trading among pension fund managers, except for small stocks. In a related study, Scharfstein and Stein (1990) explored factors contributing to herd behaviour in money managers' investment decisions (Ahmad & Wu, 2022; Quaicoe & Eleke-Aboagye, 2021). The study created a model that distinguishes between competent managers who receive informative signals about investment value and biased (dumb) managers who receive noise signals. The study has identified reputational concerns and the 'sharing-the-blame' effect as factors that could drive managers to herding behaviour.

The second approach, "Market-wide herding", focuses on the behaviour of all participants toward the market as a whole. Christie and Huang (1995) introduced the Cross-Sectional Standard Deviation (CSSD) as a tool to examine the US market. For their study, they analysed the daily closing prices of both the market and individual stocks. The CSSD measures the variation between each stock's return rate and the overall market return. Significantly, the effectiveness of the CSSD is limited to situations where investors exhibit identical behavioural trends. Chang et al. (2000) introduced the Cross-Sectional Absolute Deviation (CSAD) to study herding behaviour in South Korea, Taiwan, Japan, the US, and Hong Kong markets. The study revealed herding in South Korea and Taiwan, with partial indications of herding in Japan, while finding no support for herding behaviour in the US and Hong Kong markets. The study utilised the daily, weekly, and monthly market closing prices and individual stocks to conduct the analysis. The CSAD proved to be particularly effective in detecting even slight changes in the market and exhibited greater sensitivity in identifying instances of herding behaviour. Gębka and Wohar (2013) argue that when investors overemphasise their view or focus on views dominant among a subset of actors (who may herd jointly moving in and out of positions) excessively ignoring market information, it results in increased dispersion in returns across assets leading to adverse herding as the possible explanation of negative herding, Gębka and Wohar (2013) identify localised herding, excessive "flight to quality" during market stress (Favero and Giavazzi 2002; Kaminsky et al. 2004; Baur and Lucey 2009; Berger and Turtle 2011; Davis and Madura 2012), and overconfidence (Goodfellow et al. 2009). When a subset of investors synchronously moves into (moves out of) a subset of assets, the resulting increase (decrease) in prices leads to excessive dispersion in return across assets, creating localised herding. Second, during highly volatile or turbulent times, investors may shift their capital from risky positions to more secure ones due to irrational fears, leading to very high CSAD values above rational levels. Third, high return dispersion might result from investors' overconfidence during high market returns due to their perceived ability to pick stocks or timing skills rather than market conditions.

In the Indian stock market, Kumar et al. (2016) conducted a study to examine herding behaviour in the stock market using the CSAD model from 2008 to 2015. The study also involved analysing the daily closing prices of Nifty, which serves as the benchmark index of NSE, along with the thirty-six companies that form part of it. Despite investigating various levels of herding in the Indian stock market, the study yielded no evidence of herding behaviour, even during extreme market conditions. These findings suggest that participants in the Indian stock market tend to make independent investment decisions and do not engage in herd behaviour by imitating the investment actions of their fellow investors. Ganesh et al. (2016) used the CSAD model to analyse whether industry herding behaviour existed in the Nifty 50 index from 2005 to 2015, and the analysis revealed that industry herding behaviour has no overall impact on the Indian stock market. Ansari and Ansari (2020) examined herd behaviour among lottery stocks in the Indian stock market from 2000 to 2018, and herding behaviour was not evident despite the use of CSSD and CSAD.

Furthermore, it demonstrates adverse herding. Bharti and Kumar (2020) analysed the herd behaviour of FMCG sector stocks from January 2008 to December 2018 using CSAD and Quantile regression. The study found a lack of herd behaviour during market asymmetries, severe swings, the global financial crisis, and afterwards. Papade et al. (2021) investigate market-wide herding employing observations of the Nifty 50 and Nifty 100 from 2019 to 2022 in the Indian stock market. The study examines the herding behaviour in normal and extreme market conditions across five sectors. The analysis finds no evidence of herding in the five sectors. Madaan and Shrivastava (2022) explored herding behaviour at the sector level in the stock market. Following the global financial crisis, the CSSD and CSAD models were employed to detect herding in the equity market. The CSSD model showed no evidence of herding, whereas the CSAD model showed evidence of herding in select areas of the Indian stock market. Furthermore, herding was observed in the cement and service sectors regardless of market state, trade volume, or conditional volatility.

Using the dynamic model, Bohl et al. (2016) investigated the US stock Market using the Markov Regime Switching Model from 2001 to 2010 to detect herding behaviour. The study has proved that herding behaviour is a time-varying phenomenon and rejected the previous assumption that herding is a constant over time that does not change with the state of the economy. The study found evidence of herding behaviour in the US stock market. Akinsomi et al. (2018) researched real estate investment trusts (REITs) listed in the UK. The study used static and dynamic models to analyse data from June 2004 to April 2016. Surprisingly, while the regime-switching model provided strong evidence of herding behaviour within the low-volatility regime, the static herding model did not detect any herding in the REIT markets. The study's most significant finding was that the FTSE 100 Volatility Index (UK VIX) played a crucial role in the transition from anti-herding behaviour in the high-volatility regime to herding behaviour in the low-volatility regime. This indicates that market volatility, as measured by the UK VIX, significantly impacted the prevalence of herding among investors in the UK-listed REITs during different market conditions.

Cakan et al. (2019) conducted a study focusing on the South African housing industry from 2004 to 2016 to explore the connection between economic policy uncertainty and herding behaviour in financial markets. Their research utilised both static and dynamic approaches to investigate this relationship. Interestingly, the static approach did not identify herding behaviour in the South African housing market. However, employing a two-regime Markov switching specification, the dynamic approach revealed evidence of herding only during the high volatility regime. This finding suggests that herd behaviour is primarily driven by increased market uncertainty. The study extended its analysis using quantile regressions to examine the link between policy uncertainty and herding behaviour. The results showed that higher quantiles of policy uncertainty were associated with a higher likelihood of being in the herding regime. This indicates a clear relationship between policy uncertainty and the occurrence of herding behaviour in the South African housing market. Fu and Lu (2020) examined the A-Chinese market using the CSSD and CSAD models from 1999 to 2016.

The herding was evident in volatile regimes as the Markov Regime Switching Model was employed in the study. Coskun et al. (2020) used the CSAD model and found that herding was not evident in cryptocurrency. The Ordinary Least Squares Regression, Generalised Autoregressive Conditional Heteroscedasticity (GARCH) and Time-Varying Markov-Switching were also used to analyse herding behaviour from 2013 to 2018. The anti-herding was evident during the study. Mand and Sifat (2021) investigated herding behaviour in Bursa Malaysia from 1995 to 2016 using CSSD and CSAD models. The result was inconsistent because herding was only detected in one of the models. In contrast, the two-state Markov Regime Switching model has shown that herding prevailed in the market. Furthermore, a deeper investigation was done through sector analysis and herding behaviour was found in the financial sector and large and mid-cap segments.

The literature review shows that herding behaviour may be detected through static and dynamic models. However, the results through dynamic models seem more robust as they allow for the detection of herding behaviour in different economic states. Furthermore, no previous studies have employed the dynamic model in the Indian market. The investigation will endeavour to address this methodological gap.

Research Question:
Based on the above literature review, the study found that herding behaviour in the Indian stock market has been measured through the static approach; however, recent studies pointed out that static and dynamic approaches can be employed to investigate the herding behaviour. Hence, a significant question arises: Does the state or regime change lead to herding behaviour in the Indian stock market?

Research Objectives:
To address the above research question, the study has formulated the research objective as:
To investigate the herding behaviour in the stock market using static and dynamic approaches.

Data and Materials

Data

The selection of the Nifty 100 for this study was based on its market capitalisation, which accounts for approximately 69% of the free-float market capitalisation of NSE-listed stocks. The Nifty 100 Index is the top 100 companies by market capitalisation from the Nifty 500. The dataset comprised 2,475 daily, 521 weekly, and 119 monthly closing prices for the Nifty 100 index and its constituent stocks. The data were collected from the Prowess IQ database, managed by the Centre for Monitoring the Indian Economy (CIME), covering the period from 2013 to 2023. The analysis, conducted using Stata 17 software, delved into market trends, stock performance, and various financial metrics over the specified timeframe. Although initially involving 100 companies, the dataset was refined to 81 companies after removing data with missing values, as indicated in the Appendix.

Econometric Models Estimation

Static Model

The study employed the cross-sectional absolute deviation (CSAD) model introduced by Chang et al. (2000), which centres on the relationship between CSAD and market return. Mathematically, the CSAD is expressed in the following manner:

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

In this context, $R_{i,t}$ represents the unique return of stock' i' at the time 't,' and $R_{m,t}$ represents the overall market return for the period' t.' The quantification of the individual stock return $R_{i,t}$ is delineated as follows:

$$R_{i,t} = \ln\left(\frac{P_{i,t}}{P_{i,t-1}}\right)$$

Here, $P_{i,t}$ denotes the closing price of stock' i' at time 't,' while $P_{i,t-1}$ indicates the closing price of the same stock 'i' on the previous trading day. The determination of the market return is computed as follows:

$$R_{m,t} = \frac{\sum_{i=1}^{N} R_{i,t}}{N}$$

N represent the number of firms.

The rational asset pricing model proposes a linear connection between the Cross-Sectional Absolute Deviation (CSAD), which represents the dispersion of stock returns, and the market return. This association is grounded in the distinct responses exhibited by individual stocks in response to market fluctuations, reflecting diverse investor perspectives influenced by private information. However, during periods of market instability, a non-linear and inversely correlated pattern emerges when investors consistently adhere to specific patterns. This pattern either constrains the extent of variation among stock returns or amplifies it at a decreasing rate.

Expanding on Black's conditional Capital Asset Pricing Model (CAPM) framework introduced in 1972, Chang et al. (2000) developed a subsequent model to identify instances of herding behaviour within the market. This model goes beyond the traditional linear relationships and incorporates considerations of investor behaviour during market turbulence, providing insights into how herding tendencies may impact asset pricing dynamics.

$CSAD_t = \alpha + \alpha_1 \left|R_{m,t}\right| + \alpha_2 R_{m,t}^2 + \varepsilon_t$……………….. eqn (1)

In the context provided, the variable $R_{m,t}$ denotes the prevailing market return, whereas $R_{m,t}^2$ pertains to the square of the market return. As expounded within the framework, herding tendencies manifest when the coefficient denoted as γ_2 assumes a negative value and concurrently demonstrates statistical significance. Conversely, an augmented market return aligns with an intensified dispersion among stock returns in scenarios where the absence of herding phenomena prevails.

Dynamic Model

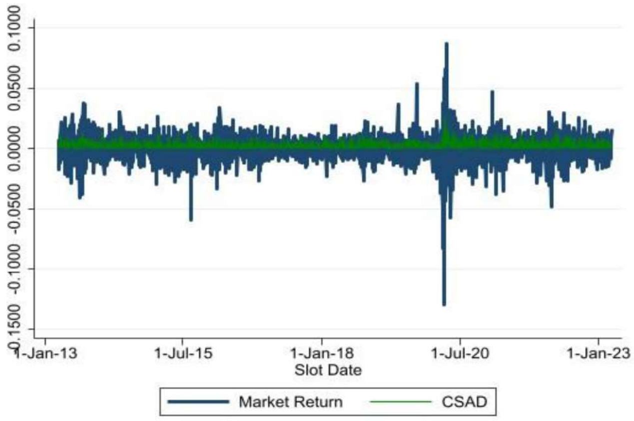
The assertion suggests that the static model presented in equation (1) may result in an inaccurate comprehension of herd behaviour, primarily because it assumes constant parameters over time, as highlighted by Balcilar et al. (2013) and Ngene et al. (2017). To address the above limitation, the study has adopted the Markov-switching model to investigate potential variations in herding behaviour across different market phases. This model is employed to estimate cross-sectional return dispersions within two states. The superiority of Markov-switching models over linear models stems from their ability to capture patterns beyond traditional stylised facts, which only non-linear models, as indicated by Babalos et al. (2015), can generate.

$CSAD_t = \alpha_{0,St} + \alpha_{1,St} \left|R_{m,t}\right| + \alpha_{2,St} R_{m,t}^2 + \varepsilon_t$……………………..eqn(2)

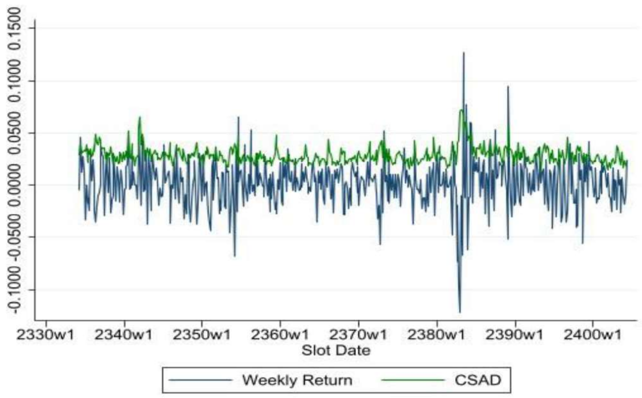
Where $\varepsilon_t \sim$ iid $(0, \sigma_{St}^2)$ and St is a discrete regime variable taking values of {0,1,2} and following a 3-State Markov process. Thus, the random variable *St* is defined as a 3-state first-order Markov chain. The specification is fulfilled by defining the transition probabilities of the Markov chain as *pij* □□*P* (*St*□1 □□*i, St* □□*j*). Thus, *pij* is the probability of being in regime *i* at time *t*+1 given that the market was in regime *j* at time *t*, where *i* and *j* take values in {0,1}. The transition probabilities satisfy $\sum_{i=1}^{1} p_{ij} = 1$.

Results and Discussions

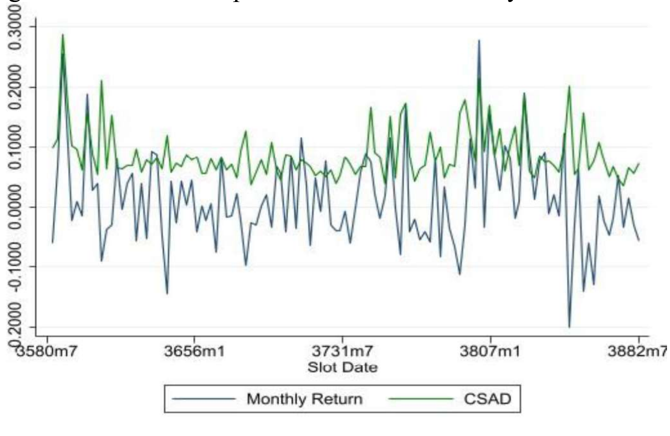
Two-way line plots between CSADs and Market Returns



Source: Estimated by the Authors
Figure 1. The two-line plot of CSADd vs Daily Market Return.



Source: Estimated by the Authors
Figure 2. The two-line plot of CSADw vs Weekly Market Return.



Source: Estimated by the Authors

Figure 3. The two-line plot of CSADm vs Monthly Return.
Figures 1,2, and 3 represent the two-way line plot of the different CSADs and Market returns for the period. High CSAD values indicate significant deviations, signalling potential market turbulence, while low values suggest greater consistency and a more synchronised market environment. Interpreting these lines together helps assess market volatility and investor behaviour, with high CSAD values, downward market trends indicating increased divergence (possibility of the herding behaviour during time), and low CSAD values coupled with upward trends suggesting market stability (in this case, the possibility of the anti-herding behaviour).

Descriptive statistics

Table No.1: Descriptive Statistics

	$CSAD_d$	Daily Return	$CSAD_w$	Weekly Return	$CSAD_m$	Monthly Return
Observation	2,475	2,475	521	521	119	119
Mean	.003092	0.005087	.028671	.002451	.0876283	.0114781
Std. dev.	.0025644	.0108197	.0081694	.0228444	.0437075	.0763913
Min	8.00e-07	-.1298046	.0140595	-.1215194	.0356509	-.1995527
Max	0.267848	.0876321	.0722565	.1271803	.288022	.2790804
Skewness	-.9456106	1.736321	1.827535	-.165794	1.803196	.0058356
Kurtosis	18.12756	9.385839	8.777991	7.114037	6.629216	.6219643
Jarque-Bera test	5449***	2.4e+04***	1015***	369.8***	129.8***	16.82***

Source: Estimated by the Authors

Note: CSADd, CSADw and CSADm represent the Cross-Sectional Absolute deviation of the daily, weekly and monthly, respectively. *** <1 %, ** <5 % and * < 10 %.

Initially, the study analysed descriptive statistics for all variables under consideration. Table 1 presents a comprehensive overview of these statistics. The findings indicated positive mean values for all variables. Additionally, the study found that all variables exhibited leptokurtic characteristics except for monthly return, which displayed a platykurtic nature. Noteworthy patterns included positive skewness across all variables, with daily and monthly returns being the exceptions, showing negative skewness. The Jarque-Bera test was applied to evaluate the normality of the variables. The null hypothesis, suggesting normal distribution when the p-value is above 0.05, was not supported, as the p-values for all variables were statistically significant at the 1% level. Although the non-normality of variables could pose challenges for the ordinary least squares (OLS) method, the central limit theorem suggests that test statistics tend to conform to appropriate distributions even in the absence of normality (Yao et al., 2014; Ansari and Ansari, 2020). Moreover, the Central Limit Theorem (CLT) asserts that sample sizes equal to or exceeding 30 are adequate, ensuring that the sample distribution approximates normality. Given the ample sample size in this study, OLS is deemed suitable for analysis.

Table No.2: The outcome of the ADF test and the Perron test for stationarity and unit roots.

	ADF Test	Philips Perron Test	
	Z(t)	Z(t)	Z(rho)
$CSAD_d$	-42.362***	-42.372***	-1856.905***
Daily Return	-47.904***	-47.974***	-1872.914***
$CSAD_w$	-12.176***	-12.649***	-257.489***
Weekly Return	-22.063***	-22.066***	-506.385***
$CSAD_m$	-9.634***	-9.818***	-119.087***
Monthly Return	-10.417***	-10.535***	-129.207***

Source: Estimated by the Authors **Note: *** <1 %, ** <5 % and * < 10 %**

The ADF and Philips-Perron tests determine and detect stationarity. Stationarity is a crucial concept in time series analysis, as it implies that the statistical properties of a time series, such as mean and variance, remain constant over time. In the context of the ADF test, the null hypothesis assumes the presence of a unit root in the time series data, indicating non-stationarity. Conversely, rejecting the null hypothesis suggests the absence of a unit root, indicating stationarity. The Philips-Perron test serves a similar purpose by examining unit roots in the time series data. It also helps identify the presence of a deterministic trend, which can affect the stationarity of the series. The outcomes of these tests are critical in time series analysis, as they guide researchers in determining whether differencing the data is necessary to achieve stationarity. Stationary time series data are essential for accurate modelling and forecasting in various fields, including economics, finance, and environmental science. Therefore, the ADF and Philips-Perron test results provide valuable insights into the characteristics of the analysed time series data. The Augmented Dickey-Fuller and Philips Perron tests were employed to check whether all variables are stationary and have a unit root. The assumptions of the Augmented Dickey-Fuller test state that if the p-value is significant at 1 %, then the null hypothesis is accepted or rejected. In Table 2, all variables are significant at 1 %. Philips Perron's test supported the results of the Augmented Dickey-Fuller test.

Static Results

Table No. 3: The outcome of the OLS regression is based on Equation 1.

Daily	Parameter	Co-efficient	Standard Error	t-Statistics	p-value
	α	.0024751(.0024751)	.0000804(.0000929)	30.80(26.65)	0.000(0.000)
	α 1	.0876984(.0876984)	.0103666(.0159343)	8.46(5.50)	0.000(0.000)
	α 2	-.3055468(-.30554)	.1692299(.3860583)	-1.81(-0.79)	0.071(0.429)
	Adjusted R-Square = 0.0506		Prob > F = 0.0000		
Weekly	Parameter	Co-efficient	Standard Error	t-Statistics	p-value
	α	.0252198(.0252198)	.0005731(.0005395)	44.00(46.75)	0.000(0.000)
	α_1	.1505029(.1505029)	.0408982(.0380048)	3.44(3.96)	0.001(0.000)
	α_2	1.687973(1.687973)	.4899922(.4062437)	3.68(4.16)	0.000(0.000)
	Adjusted R-Square = 0.2808		Prob > F = 0.0000		
Monthly	Parameter	Co-efficient	Standard Error	t-Statistics	p-value
	α	.0658588(.0658588)	.0059332(.0055542)	11.10(11.86)	0.000(0.000)
	α 1	.1600786(.1600786)	.14802(.1779946)	1.08(0.90)	0.282(0.370)
	α 2	2.10232(2.10232)	.6570289(.9462186)	3.20(2.22)	0.002(0.028)
	Adjusted R-Square = 0.5118		Prob > F = 0.0000		

Source: Author's Calculation

Note: The figures within the parentheses represent the regression results with Newey-West standard errors.

The rational asset pricing theories (CAPM) state that a linear relationship exists between the CSAD and the market return since individual securities react differently to the market return to replicate investors' beliefs based on their private information. However, Chang et al. (2000) stated that the herd behaviour of the investors reduces the dispersion among the stock returns or increases it at a decreasing rate. Hence, a negative and non-linear relationship exists between the CSAD and market return in the case of herd behaviour among the investors. Table 3 depicts the outcome regression results based on Equation 1. The study found the issue of heteroskedasticity and autocorrelation daily, weekly, and monthly. A robust test has been run to rectify the above problem, and the results are depicted within the table's parentheses. The coefficient of Rmt2 was positive but insignificant for the daily data series.

In contrast, the weekly and monthly data series were positively significant at 1 %. The study found adverse or anti-herding patterns in the weekly and monthly datasets. Gębka and Wohar (2013) argue that when investors overemphasise their views or focus on ideas dominant among the subset of actors (who may herd jointly moving in and out of positions), excessively ignoring market information, it results in increased dispersion in returns across assets, leading to adverse herding. When a subset of investors synchronously moves into (moves out of) a subset of assets, the resulting increase (decrease) in prices leads to excessive dispersion in return across assets, creating localised herding. The study aligns with the findings of Satish and Padmashree (2018), Kanojia et al. (2020), and Garg & Gulati (2013). However, it differs from the conclusions drawn by Banerjee and Padhan (2017), Shrotryia & Kalra (2020), and Kumar et al. (2016). According to Kanojia et al. (2020), the prevalence of herding behaviour in the Indian market can be attributed to the significant influence of institutional investors and the comparatively low involvement of individual investors in the market. Garg & Gulati (2013) argued that due to the regulatory reforms implemented in the Indian equity market and the substantial involvement of foreign institutional investors, there is a perception that investors' behaviour has become more rational, and rational pricing models have been followed in Indian stock markets. It may also highlight the weakness of the static model, which fails to capture the potentially dynamic nature of the herding behaviour, thus providing further support for a model that allows testing of herding under different market regimes in which herding behaviour

May or may not exist.

Dynamic Result

Table No.4: The outcome of the Markov-Regime Switching Model based on Equation 2.

Daily	Parameter	Co-efficient	Standard Error	t-Statistics	p-value
State1	α	.0021587***	.000075	28.80	0.000
	α_1	.0512831***	.0092755	5.53	0.000
	α_2	-.2900586**	.1338724	-2.17	0.030
State 2	α	.0067807***	.0002829	23.97	0.000
	α_1	.1368838***	.031106	4.40	0.000
	α_2	.2590481	.5465748	0.47	0.636
AIC	HQIC	SBIC	sigma	P11	P21
-9.3207	-9.3130	-9.2996	.0018147	.9035874	.8091579
Weekly	Parameter	Co-efficient	Standard Error	t-Statistics	p-value
State1	α	.0249436***	.0005157	48.37	0.000
	α_1	.1206369**	.0420127	20.87	0.004
	α_2	1.721285**	.6486998	2.65	0.008
State 2	α	.0473239***	.0026441	17.90	0.000
	α_1	.0521099	.1309988	0.40	0.691
	α_2	.8847416	1.056116	0.84	0.402
AIC	HQIC	SBIC	sigma	P11	P21
-7.3270	-7.2982	-7.2535	.0057783	.9917019	.1889679
Monthly	Parameter	Co-efficient	Standard Error	t-Statistics	p-value
State1	α	.0641418***	.0045906	13.97	0.000
	α_1	.0241097***	.1283106	0.19	0.000
	α_2	2.357183	.5248997	4.49	0.851
State 2	α	.1517173***	.0211379	7.18	0.000
	α_1	-.1936934	.4264409	-0.45	0.650
	α_2	2.682086***	1.439701	1.86	0.000
AIC	HQIC	SBIC	sigma	P11	P21
-4.2585	-4.1732	-4.0483	.02005	.8971198	.80553358

Source: Author's Calculation **Note: *** <1 %, ** <5 % and * < 10 %**

In the context of the static model, herding behaviour was not evident; instead, there was a prevalence of anti-herding or adverse herding during the study period. Building upon the study by Mand & Sifat (2021) and Cakan et al. (2019), the study employed a two-state Markov Regime Switching model. Table 4 reveals that the coefficient was negatively significant at the 1% level in state 2 for the daily dataset. It suggests that investors tend to imitate the actions of other investors, and such behaviour varies depending on the state or regime. Contrary to the prior assumption of herding as a constant phenomenon that does not change with the state of the economy, Bohl et al. (2016) argued that herding behaviour is a time-varying phenomenon.

Similarly, in the studies by Mand & Sifat (2021) and Cakan et al. (2019), herding was observed with changes in state or regime, contradicting the analyses of Kanojia et al. (2020) and Garg & Gulati (2013). Arjoon and Bharatnagar (2017) suggested that a time-varying analysis reveals the evolving nature of herding, indicating that an approach based on constant coefficients can only provide partial information about such behaviour. Given the dynamic and unpredictable nature of investors' behaviours, these expected results are influenced by changing sentiments, preferences, biases, and economic fundamentals. In this context, according to (Economou et al.,2011; Holmes et al., 2013; Guney et al.,2016; and Youssef & Mokni,2018), the presence of herding behaviour can manifest itself according to the market volatility state. Indeed, during low volatility periods, investors herd based on the assumption that it is easy for an investor to mimic their peers during these periods.

In the weekly dataset, the coefficient is positively significant at the 10% level in state 1, indicating the presence of anti-herding behaviour. Furthermore, anti-herding was evident in the monthly dataset as the coefficient was positively significant at 1% and 10 % in States 1 and 2, respectively. Tan et al. (2008) suggested that herding behaviour is more prevalent in the high-frequency datasets. The study is in line with Tan et al. (2008), Youssef & Mokni (2018), and Ansari and Ansari (2020). The transitional probabilities from State 1 to State 2 suggest that the low-volatility regime (i.e. regime 1) follows the low-volatility regime, and the high-volatility regime (i.e.

regime 2) follows the high-volatility regime. In other words, the market is likelier to follow this risky and high-volatility regime during extreme market returns and large price movements. On the other hand, in high volatility regimes, anti-herding behaviour occurs in the market.

Conclusions

Understanding the behavioural aspects of investor decision-making can help market participants, financial advisors, and policymakers develop strategies to mitigate the impact of cognitive biases and improve overall financial decision outcomes. Regulators may be grappling with integrating behavioural finance insights into regulations. The rise of robo-advisors and algorithmic trading raises ethical questions about how these technologies account for and respond to behavioural biases. The primary objective of this study was to examine herding behaviour within the Indian stock market, spanning the period from 2013 to 2023. The study gathered data on the daily, weekly, and monthly closing prices of the Nifty 100 index and its component stocks. The dataset was sourced from the Prowess IQ database, managed by the Centre for Monitoring the Indian Economy (CMIE). The study utilised the Cross-Sectional Absolute Deviation (CSAD) model, developed by Chang et al. (2000), to identify herding behaviour. Two distinct approaches were employed to explore herding behaviour: static and dynamic models. The static model used Ordinary Least Squares (OLS) regression for analysis. In contrast, the dynamic models utilised Markov regime-switching models, as introduced by Hamilton in 1989. These methodologies were applied to gain insights into the presence and nature of herding behaviour in the Indian stock market during the different regimes.

The study's significant findings reveal that the herding pattern does not prevail in the static model, whereas the anti-herding pattern was exhibited. The herding and anti-herding patterns are typically related to behaviours in financial markets or decision-making processes where individuals tend to follow the crowd (herding) or intentionally go against the crowd (anti-herding). In a herding pattern, individuals tend to mimic the actions or decisions of others, leading to collective behaviour that follows a trend. This behaviour may be driven by a desire for conformity, fear of missing out (FOMO), or a belief that others possess valuable information. On the other hand, an anti-herding pattern involves individuals intentionally making decisions that go against the prevailing trend. This behaviour may be motivated by contrarian strategies, where individuals believe the crowd is wrong and purposely choose to do the opposite. Psychological factors, such as risk aversion or a desire for independence, could contribute to an anti-herding pattern in the static model. The dynamic model approach yields results contradicting the static model. The dynamic model results suggested that herding was evident in daily data, whereas the anti-herding pattern was evident in weekly and monthly data.

Policymakers may be considering strategies to manage the impact of herding on market stability and investor outcomes. Policymakers might explore ways to improve communication and disclosure practices to account for behavioural biases. This includes designing disclosures more likely to be understood and acted upon by investors. Policymakers and regulators may be examining how to balance the need for short-term economic stability with encouraging long-term decision-making by investors. Behavioural biases often lead to a focus on short-term gains or losses. Unforeseen global events, such as financial crises or pandemics, can significantly influence investor behaviour. Policymakers may need to adapt their strategies to address the specific behavioural challenges such events pose.

Limitations and future scope

In this study, investor behaviour regarding the extreme market conditions has not been measured, whereas previous studies have measured it. Moreover, the study has not considered bullish or bearish market conditions. The study only considered the NSE-100 rather than the whole NSE or BSE market. The study did not consider the factors that might influence investors to herd. For future studies, various economic variables can be considered as to how such variables lead investors to herd. Furthermore, the intensity of the herding can be measured using the study of Hwang and Solomon (2004), as the herding behaviour prevailed during the study.

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