Herding in Factor Portfolios: A Regime-Switching Perspective on the Indian Market

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ABSTRACT

The current research investigated dynamic herd behavior in different factor portfolios for the Indian Stock Market. The study is conducted on three factors: market size, volume and profit-book ratio from 2009-2023. Using the three-regime Markov model, the study documented notable results. We observed herding for large, high-volume, and value stocks with extremely high volatile regimes. These results exhibit that the type of stocks matters while investing in the stock markets. Investors behave differently for various types of stocks and impact the market trend, especially in times of unprecedented situations. These results have implications for investors, market regulators, and portfolio managers.

KEYWORDS

Herd behavior, Markov Regime Switching model, Volatility, Market Size, Volume, Value/Growth Stocks

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INTRODUCTION

In past years, behavioral finance has become the most interesting research domain for researchers. Behavioral finance entails market inefficiency and irrationality against the efficient market hypothesis (Sharma & Kumar, 2020). Investors react irrationally because of various behavioral biases like recency bias, overconfidence bias, loss aversion bias and herd behavior, etc. Investors start acting irrationally because of these anomalies, leading to stock market bubbles, high market fluctuations, and momentum in the stock market (Kapoor & Prosad, 2017). Herding is one of the most common and observed biases in the financial market, where investors imitate the actions of similar types of investors, leading to trends in market prices. There are many causes behind herd behavior, which can be deduced from a theoretical framework. Numerous prior studies have elucidated the emergence of herding behavior, highlighting several key contributing factors. These include reputational concerns, the phenomenon of informational cascades, the superiority of certain information, and the complexities inherent in the informational structure of the environment. (Avery & Zemsky, 1998; Bikhchandani et al., 1992; Scharfstein & Stein, 1990). Studying herding behavior is crucial as it can lead to volatility in the market, widening the disparity between the market price and the intrinsic value of any stock, and potentially leading to a bubble-like scenario in the financial markets (Bikhchandani et al., 1992; Chiang & Zheng, 2010). Hence, it is vital to explore similarities among the trading behavior of Indian investors.

An understanding of the herd behavior encourages better investment decisions with portfolio diversification. So, with this objective, we examine dynamic herding in the Indian stock market from January 2009 to March 2023. Time-varying herding refers to the phenomenon of investors showing patterns of imitations, and these patterns change according to time. The ever-changing aspect of herding will shift when new information enters the market, superseding outdated information. There are several reasons for selecting the Indian stock market. To begin with, emerging economies such as India exhibit herding behavior due to cultural variances, inadequate enforcement of laws, and investors who are uneducated and uninformed.(Chang et al., 2000; Kanojia et al., 2022; Lao & Singh, 2011). Next, India is a rapidly growing economy among emerging markets, characterized by increasingly relaxed regulations on foreign investment. This has resulted in a significant influx of Foreign Institutional Investment (FII) into the country. Consequently, it has been noted that during periods of high market volatility, investors tend to mirror the actions of FIIs and align their movements accordingly. This study contributes various insights to the body of literature on herding behavior. To begin with, the current research utilized a Regime Switching constant probability model, incorporating three Markov states, to analyze the Indian stock market for the presence of herd behavior. The three-regime model allows for the exploration of the dynamic characteristics of cross-sectional dispersion and the impact of various structural breaks or events on the migration of the data into different regimes or states where herd behavior can be detected (Balcilar et al., 2013). Firstly, there has been limited research that examines the important autocorrelation feature of cross-sectional absolute deviation within a time-varying framework, and this research incorporates two lagged terms of the explained variable in the Regime model. In this analysis, we investigate the significant influence of volatility on herding behavior in three different portfolios.

This research is specifically focused on studying dynamic herding in different factor portfolios. We have examined dynamic herding in three factors i.e.: size, volume, and book-to-profit ratio. For bifurcating the sample into different portfolios, we have applied the methodology of Fama and French (2015).

The investigation of time-varying herding has implications for policymakers and market participants by helping them identify the potential market risk associated with the presence of herding. Moreover, strategies can be formed based on identifying dynamic herding to maintain financial stability and market efficiency. The structure of the paper is as follows: Section 2 includes the relevant previous research. The empirical framework is outlined in Section 3. Section 4 analyzes the findings and interpretations, while Section 5 provides the concluding observations and recommendations for the study.

REVIEW OF LITERATURE

This section provides a detailed review of previous studies that showed the existence or absence of Herd Behavior in the Financial Market.

2.1 Herding in the Financial Market

Herd Behavior is a biasness that makes the investors irrational and prone to risk. Hence, it is necessary to estimate the herding in the financial market. Literature depicts two strands of literature that estimate uniformity in the equity market. One strand of literature is related to measuring herding among individual market participants like individual investors, institutional investors, etc. This type of herding can be measured using a model devised by Lakonishok et al. (1992). While another strand measured herding in the whole market using the cross-sectional standard and absolute deviation. This model was developed by Christie and Huang (1995) and later on modified by Chang et al. (2000) who stated the linear and positive relationship between absolute market return and dispersion but this relationship becomes nonlinear and negative at the time of crowd behavior.

Many empirical studies have investigated herding using the cross-sectional absolute dispersion. Gleason et al. (2004) conducted a study on herd behavior by analyzing intraday data from sector-specific exchange-traded funds during periods of extreme volatility in the American stock exchange. Their findings shed light on how investors often act collectively, particularly in turbulent market conditions. They applied both cross-sectional standard deviation and absolute deviation. Results exhibited insignificant herding in sectoral ETFs. Tan et al. (2008) explored the phenomenon of herd behavior within the context of Chinese A and B shares, which are traded on the Shanghai and Shenzhen stock exchanges. Utilizing the cross-sectional absolute deviation (CSAD) method, they aimed to analyze how investors' collective actions influenced stock market trends and prices, highlighting the dynamics of investor sentiment in these Chinese markets. Overall results exhibited daily herding in both the A-share and B-share markets, while weaker evidences of herding are found for monthly and weekly data. Moreover, asymmetries in herd behavior are also examined based on market returns, volume, and volatility. Evidence of significant herding is found during rising market returns, high volume, and higher volatility periods in all the markets. However, herding is stronger in the Shanghai A-share market as compared to the B-share market. Benkraiem et al. (2019) checked out herding in listed SMEs in French and UK equity markets for the period 2005-2016. Results revealed that uniformity is stronger in micro-cap in both the markets as compared to the large-cap. It depicts small-cap companies exhibiting a higher intensity of herding as compared to large-cap companies. Choi and Yoon (2020) detected uniformity in the Korean KOSDAQ and KOSPI markets using Quantile regression and a linear approach. The analysis utilized a daily series of the data spanning from 2003 to 2018. Results showed herding in the down market according to the CSAD approach while quantile regression results reveal significant herding in upper and lower quantiles. They also noted evidence of negative herding using a quantile regression approach. This indicates that herding is the phenomenon of extreme market conditions. Investors react quickly during these uncertain situations.

Similarly, Benkraiem et al. (2021) examined uniform behavior in the French and UK by incorporating a linear approach. The study relates herding between listed small and medium enterprises and large stock companies. Results exhibit herding in small-cap companies in the tranquil period as compared to no herding in the uncertain period. Kanojia et al., (2022) have studied static herding in the Indian stock market for the time spanning from 2009 to 2018 exhibiting insignificant herding among Indian market participants.

The literature reveals that numerous studies have employed the linear regression method to scrutinize herding behavior, yielding mixed results regarding its presence or absence in financial stock markets; later on, the studies shifted their focus toward identifying the dynamic nature of herding. Hwang and Salmon (2004) first explored a model for identifying dynamic herding by deploying Kalman's filter state space model. They argued that betas can change over time and proposed a time-varying model to measure herding using monthly betas. The proposed model is tested on two countries, namely the US and South Korea, showing evidence of significant herding during normal periods. The research showed that the market began to exhibit efficiency during times of crisis. Herding is typically a temporary occurrence assessed through daily or intraday data, as it tends to arise in extreme market conditions (Gleason et al., 2004). By keeping in mind the short-term presence of herding, Klein (2013) identified the time-varying herding using the Markov switching model by bifurcating the market into two regimes, namely turmoil and tranquil regimes. They analyzed herding in European and the US markets from 2001-2011. The findings of the study reflect uniform trading in both markets during turmoil regimes as compared to tranquil regimes. Balcilar et al. (2013) also examined dynamic herding in the Gulf countries by utilizing the Markov model. Their research revealed three distinct market regimes: low, high, and crash regimes. The study's findings indicate that herding occurs in the crash regime, highlighting its presence during extreme market movements.

Similarly, researchers have examined the importance of exploring dynamic herding and many studies further scrutinize dynamic herding in different financial markets. like Babalos et al (2015) studied crowd behavior in the real estate markets in the US by using a regime model. They evidenced the presence of herding during the crash regime as compared to no herding in the static model. Later on a study by Bohl et al. (2016) observe that many studies have ignored the time-varying concept in transition probabilities while estimating dynamic herding using the regime model. In a highly volatile regime, anti-herding in the US stock market reveals that investors focus on fundamentals rather than following the crowd during extreme movements. This suggests a more rational approach to navigating market fluctuations. Similarly, Stavroyiannis and Babalos (2020) also inspected the herding coefficients in the Eurozone stock market but with a time-varying effect. They have also considered stochastic volatility to be time-varying. The study's results indicated the presence of anti-herding, also known as negative herding.

Fu and Wu (2021) investigated herd formation in the Chinese equity market by deploying the Markov model. In the Chinese market, researchers discovered two distinct regimes: a high volatile regime and a low-volatile regime. Their findings demonstrated that herd behavior thrives in the highly volatile landscape, while adverse herding emerges in the calmer, low-volatility regime. This insight highlights the crucial dynamics at play in market behavior, offering valuable implications for investors and traders alike. Results also indicated a stronger level of herding for large-cap stocks, value stocks, and high trading volume. Mand and Sifat (2021) detected significant evidence of herd formation in Malaysia using a regime model in the highly volatile regime. The studies indicate that herding behavior tends to exaggerate significantly during periods of uncertainty in the majority of financial markets. This suggests that market participants are more likely to follow the crowd when uncertainty is elevated, making it crucial for investors to be aware of this tendency. In a similar manner, Yamaka et al. (2021) explore herding in the Japanese stock market using both CSAD and Markov switching approaches. They divided the market into two regimes, specifically the up and down-market regimes. They provided evidence for significant herding in the up-market regime against no herding in the down-market regime. The paper of Yang and Chuang (2023) studied the time-varying herding in the US, China, and Taiwan stock markets during various events. The results of their study mention the evidence of anti-herding in all the chosen stock markets after 2010. They also found the existence of different herding states through their proposed model. Likewise, the recent study of Javaira et al. (2024) investigated the dynamic herding and volatility relationship during COVID-19 in developed countries. Their study employed the Markov regime switching model and found that investors switch from anti-herding to herding-like situations at the time of unprecedented crises. The study of Rubbaniy et al. (2025) tested the various dynamics in energy stock markets. They used the state space model and quantile on quantile regression models to test fundamental and intentional herding. Findings elaborate on the evidence of intentional herding in North American energy stocks.

2.2 Indian-specific Evidence on Herding

There exists a substantial body of works regarding herding behavior in the Indian stock market, which presents a range of findings that indicate both the presence and absence of such behavior. Many studies have used static models to analyze herding among Indian market participants. Lao and Singh (2011) analyzed the herding behavior in the Chinese and Indian stock markets from 1999 to 2009 through the CSAD approach, revealing crucial trends and insights that can inform future investment strategies. The results from various studies demonstrate herding behavior in stock markets, with particularly greater intensity noted in the Chinese stock market. Garg and Gulati (2013) conducted an analysis of herding behavior in the Indian share market using a comprehensive dataset encompassing daily, monthly, and weekly data from the National Stock Exchange spanning from 2000 to 2013. The findings indicate that there is a notable absence of herding behavior in the Indian stock market, even in uncertain situations, such as significant fluctuations in trading volume and market trends. Building on this, Poshakwale and Mandal (2014) employed the Kalman filter methodology to further investigate herding in the Indian financial market. Their study incorporated time-varying state variables, including market volatility and directional trends, and highlighted significant evidence of herd instinct, particularly during bear market conditions. Furthermore, Kumar et al. (2016) documented no herding among Indian stock market participants during the bull and bear phases as well as under extreme market conditions. It conveys that investors in the Indian market tend to rely on the fundamental analysis of companies rather than succumbing to the influence of market events. Supporting this perspective, Ganesh et al. (2017) analyzed uniform behavior in the Indian stock markets from 2005 to 2015 and concluded that herding behavior was largely absent, with notable exceptions in the years 2011 and 2014. Collectively, the above results contribute to the understanding of behavioral dynamics in emerging markets and their implications for investment strategies. Recently, the study of Ansari and Ansari (2021) measured herding for the period 207-2018 using the static model in normal and bull/bear phases. Their findings showed the anti-herding in Indian market in all market conditions. Similarly, the study conducted by Kanojia et al. (2022) reveals no herd formation within the Indian capital market, as evidenced by the application of the CSAD methodology over the period from 2009 to 2018. The findings indicate a consistent absence of herding across varying market conditions. This comprehensive literature review highlights that a majority of scholarly analyses about the Indian market have demonstrated a lack of herding tendencies when employing static models. Collectively, these studies suggest that the Indian stock market operates with a degree of efficiency, where investors are inclined to make rational and informed decisions.

2.3 Research Gap

The examination of literature indicates that the Indian market presents conflicting evidence regarding the existence of herding. The existing researches has employed a static method to assess herding, primarily focusing on the analysis of herding during rising or falling market conditions. Despite the significant advancements in regulatory frameworks for investment following the liberalization of the Indian market, India remains an emerging economy characterized by a substantial population of small retail investors. These investors often exhibit irrational behaviors during periods of extreme market volatility, complicating investment dynamics and overall market stability. (Ansari & Ansari, 2021). Additionally, in the past decade, the Indian stock market has seen an increased participation of foreign institutional investors, which has made it susceptible to different investor emotions such as herd behavior and positive feedback trading (Mukherjee & Tiwari, 2022). Furthermore, the arrival of extraordinary occurrences such as COVID-19 has greatly amplified inefficiencies in the Indian stock market (Bhatia, 2022). As a result, domestic investors increasingly mirrored the actions of foreign investors, illustrating the ripple effect of global market dynamics. All these above-mentioned reasons make the study useful to explore whether, with time, herding behavior has evolved in the Indian market or vanished. The present research is unlike the recent study of Ansari and Ansari (2021) in several ways. First, they tested herding in the up/

down market, but we have analyzed herding with special reference to volatility. First, they applied the static model to assess herding, whereas we investigate the time-varying herding within a three-regime framework. Although the of Poshakwale and Mandal (2014) explored herd mentality by applying the Kalman filter witstudy hin the National Stock Exchange of India, utilizing monthly beta instead of daily or intraday data. The study of Kabir and Shakur (2018) investigated the consistency in both high and low-volatile regimes across various countries, including India, utilizing the Smooth transition model. However, this study is different from their study in the methodological framework by incorporating three regime specifications using the Markov regime-switching model. This study investigates herding behavior across various factor portfolios, including size, volume, and book-to-market ratio.

RESEARCH METHODOLOGY

It describes the methodology adopted to test the herding and Herding Intensity in the Indian Stock Market. First, the data is collected from the Prowess IQ database. Then, data filtration is performed using the linear interpolation method to replace the missing values. After that, the dependent variable, i.e., Market Return, is calculated by taking an equal-weighted average of the daily logged values of individual stock market returns on a day t of all companies listed in the S & P BSE 500 index. Then, the dependent variable, i.e., Cross-sectional Absolute Deviation, is calculated. In the next step, a linear OLS regression is performed on the time series variables using E-view 9.0. To evaluate the dynamic herding from 2009 to 2023, the Markov Regime switching model is employed. However, prior to that, non-linearity is examined within the model. Then, the number of Regimes is identified using various criteria. Herding is tested for different factor portfolios, like Large/Small-cap stocks, value/Growth stocks, and high/low volume stocks, using the regime model. The work of Fama and French (1995, 2015) has been used for bifurcating different stocks into different portfolios. A detailed explanation of data and the econometric framework is provided in the various sub-sections.

3.1 Data

This section explains the data and their properties used in the study, which will guide the analytical work of the study.

3.1.1 Sources of data

This study examines herd behavior within the overall market and across various market portfolios, specifically focusing on size portfolios, volume-based portfolios, and price-to-book ratios. The dataset consists of daily adjusted closing prices, annual market capitalization, yearly price-to-book ratios, and the annual number of shares traded by companies listed in the S&P BSE 500. The S&P BSE 500 serves as a significant index representing all 20 large industries within the economy. As a market capitalization-weighted index, it accounts for approximately 93% of the total market size of the Bombay Stock Exchange (BSE) (www.moneycontol.com, 2021). Daily data may be regarded as high-frequency data in certain situations since it offers greater accuracy than weekly or monthly data (Hung, 2019; Jebran & Iqbal, 2016). When using weekly or monthly data, valuable information can be lost since it averages out daily fluctuations. While numerous studies have treated intraday data as high-frequency due to constraints related to time and data availability, this research regards daily data as the next best option to high-frequency data, as it can illustrate volatility more distinctly than lower-frequency data. The information utilized in this study was sourced from the Prowess IQ database, provided by the Centre for Monitoring Indian Economy (CMIE). The companies that have missing values of more than 10 per cent of the total number of observations, are also excluded. Furthermore, for the companies that have missing values of less than 10 per cent, data for those companies are replaced using linear interpolation (Mertler et al., 2021). Linear interpolation is a type of imputation technique that replaces the missing values linearly in increasing order. This research applied linear interpolation instead of the average value method because the mean method provides a large number of errors as related to the mean value method (Noor et al., 2015). In the evaluation of herding behavior across different portfolios, the number of companies involved in the study varies. For the market-cap and volume-based portfolios, a total of 337 companies have been analyzed, those companies are excluded from the study that have not traded from the beginning to end of the study period i.e., 2009-2023. Companies lacking yearly September data on volume and market capitalization are excluded from this portion of the analysis. In contrast, the price-to-book ratio portfolio consists of 320 companies. Within this portfolio, companies not having march data related to price-to-book ratio are omitted from consideration. Furthermore, companies demonstrating negative book values are eliminated from the price-to-book ratio portfolio analysis Fama and French (1995). The criteria for making a single sorted portfolio are taken from the study of Fama & French (1995, 1996). For analytical work, we have used E-views 9.0, MS-Excel, R, SPSS 25 and Ox-metrics 7.0.

3.1.2 Period of the study

The study collected data for almost 15 years from January 2009 to March 2023. The reason for selecting this study period is that it encompasses many crucial events and impacts that might affect the Indian economy.

3.2 Econometric Framework

This section describes the econometrics models used to investigate herding in the Indian stock market.

Static Measure

The static measure pertains to the analysis of linear market-wide herding phenomena. The model established by Christie and Huang (1995) posits that at extreme market movements or heightened market stress, distinct stakeholders are prone to subordinating their independent opinions in favor of prevailing market consensus. This behavior results in a convergence of actions among investors, creating a herd-like formation. Consequently, this herding behavior affects market dynamics, where individual stock returns become increasingly aligned with aggregate market returns, leading to a reduction in dispersion. Christie and Huang make a cross-sectional standard deviation as a metric for quantifying uniform behavior during periods of uncertainty, with the dispersion calculation being delineated as follows:

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

CSSDt is the cross-sectional standard deviation. $R_{i,t}$ is the individual stock returns on a day t, $R_{m,t}$ is the cross-sectional average of stock returns on a day t. N is the total number of firms on a day t. The Study calculated equal weighted market return instead of market-cap weighted market return because, from our analysis, we detected that Indian companies yield similar results in both cases for large samples. The research utilized a market return proxy that assigned equal weights to every stock in the portfolio, which has also been calculated by various studies (Chang et al., 2000; Chiang & Zheng, 2010; Garg & Gulati, 2013; Kanojia et al., 2022). That is why, we did not calculate market-cap weighted market return. If dispersion is lower, then it depicts anti-herding. In share market analysis, a diminished dispersion in asset returns may suggest the presence of crowd behavior among stakeholders. Nevertheless, it is crucial to note that lower dispersion does not automatically imply herding is occurring. During an uncertain period, the rational asset pricing model posits that individual stock returns react with varying sensitivities to the prevailing market environment. This disparity in sensitivity tends to amplify dispersion, reflecting the diverse responses of market participants and reinforcing the notion of potential deviations from fundamental valuations. But at the time of herd behavior, this dispersion starts decreasing. They tested herding during market stress using the following regression model:

$$CSSD_t = \alpha + \beta_t^{dn} D_t^{dn} + \beta_t^{up} D_t^{up} + \varepsilon_t \quad (2)$$

D_t^{dn} is the dummy variable at a time t when the market return is in the extreme lower tails of the distribution. D_t^{up} is the dummy variable at a time t when the market return is in the extreme upper tail of the distribution. In the presence of herd behavior, the coefficients β_t^{dn} and β_t^{up} is become negative. To define the upper and lower tail, CH used the 1 and 5 per cent criteria of the total number of observations. Subsequently, the CH (Christie and Huang) model was refined by Chang et al. (2000), who posited that the traditional rational asset pricing model not only characterizes a positive association between market return dispersion and absolute market return but that this relationship also follows a linear trajectory. However, in scenarios where herd behavior is present, this relationship becomes both decreasing and non-linear. They originated a model grounded in the capital asset pricing framework that delineates an increasing and linear relationship between cross-sectional absolute deviation (CSAD) and market return. They introduced a non-linear term within the regression model to identify the effects of herding behavior and concluded that CSAD tends to increase at a diminishing rate or decrease when herding is significant. The methodology for calculating CSAD along with the model specification is outlined as follows:

$$CSAD_t = \frac{1}{N}\sum_{i=1}^{N}\left|R_{i,t} - R_{m,t}\right| \quad (3)$$

In this context, CSAD (Cross-Sectional Absolute Deviation) is defined as dispersion's measure of individual stock returns. It is analyzed as the absolute deviation of individual stock returns from the equally weighted cross-sectional average of n returns at time t. N represents the number of firms considered at time t.

$$CSAD_t = \gamma_0 + \gamma_1\left|R_{m,t}\right| + \gamma_2\left(R_{m,t}\right)^2 + \varepsilon_t \quad (4)$$

The above regression model is a basic model used to test the herding in normal situations for all stocks. $|R_{m,t}|$ is the absolute market return, and $(R_{m,t})^2$ is the squared market return. The increasing and linear relationship can be established through the positive coefficient 1. During periods of herding, the association among the variables transitions to a non-linear and negative correlation, resulting in a significantly negative coefficient. the coefficient 2 becomes significantly negative.

We have used the above regression model with some modifications to examine the presence or absence of herding. Our model is as follows:

$$CSAD_t = \gamma_0 + \gamma_1\left|R_{m,t}\right| + \gamma_2\left(R_{m,t} - \overline{R}_m\right)^2 + \gamma_3 CSAD_{t-1} + \gamma_4 CSAD_{t-2} + \varepsilon_t \quad (5)$$

The presence of absolute market return and squared market return in the same model leads to a high level of multicollinearity, which needs to be addressed in the OLS models. To address the issue of multicollinearity, we refer to the research conducted by Yao et al. (2014), which starts by determining the squared deviation of market returns by taking the difference between the actual market returns and their mean. Furthermore, the research incorporates a two-lag term for the dispersion variable within the model to effectively account for the substantial autocorrelation properties observed in dispersion data. The decision to include only two lag terms is based on empirical observations indicating that higher-order lag terms do not enhance the robustness of the results (Lao & Singh, 2011). Many empirical studies included lag terms in their model to remove the autocorrelation. The analysis employed standard errors that are consistent with heteroscedasticity and autocorrelation, following the methodology established by Newey and West (1987). Additionally, a lag term of the response variable was incorporated to accurately estimate the regression coefficients

- **Non-linearity Test**

In interpreting the results, if the critical value is higher than the test statistic, we fail to reject the null hypothesis, suggesting non-stationarity in the series. Conversely, if the test statistic exceeds the critical value, we reject the null hypothesis, concluding stationarity in the data.

- **Likelihood Ratio Test**

It involves testing whether the maximized log-likelihood function is falling sharply after imposing non-linear restrictions on data. It includes the following steps:

1. Calculating maximized log-likelihood for both constrained and unconstrained models. Note that the likelihood value for the unconstrained model is always at least greater or equal to the restricted model (Brooks, 2008).

2. After that we have calculated the likelihood ratio statistic using the formula as per equation (6)

$$LR = -2(L_r - L_u) \sim x^2(m) \quad (6)$$

Here, m is number of restrictions

3. In the Regime model, there is an incidence of unidentified nuisance parameters under the null hypothesis (Brooks, 2008), hence standard distribution does not apply to the regime model.

So we have also reported the p-values calculated using the approximate upper bound test proposed by Davies (1987). This test is performed in R.

b. **Time-varying Measure**

In time series analysis, non-linear structures often preclude the practical application of linear models. These models fail to adequately capture important financial data characteristics, such as leptokurtosis, volatility clustering, and leverage effects (Brooks, 2008). A non-linear data generating process means the current series is related non-linearly to the current and previous value of the error term (Campbell et al., 1997). Various non-linear models have been developed to address these complexities, specifically focusing on non-linearities in either the mean or the variance. For instance, Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models exhibit non-linearity in variance, while switching models adapt their behavior based on different time points, thereby accommodating the dynamic nature of financial markets.

- **Markov Regime Switching Model**

Sometimes, a change in financial time series is permanent or temporary. When there is a change in the behavior of a series at one time, and again, the series reverts to its original nature; this is called regime shift. Regime changes can be of two types: Markov regime shifts and threshold autoregressive models (Brooks, 2019).

In Markov regime models, there is a presence of m number of regimes or states based on the Markov Property. The Markov property asserts that the transition probability to any future state t+1 is determined solely by the current state at time t, without consideration of preceding states. This concept can be articulated mathematically as follows:

$$P\left(y_0,\ y_1,\ y_2 \ldots\ldots\ldots y_t\right) = P\left(y_{t+1} | y_t\right) \quad (7)$$

In the Markov Regime model, regime-switching may occur at both the average and standard deviation of the error term. First Hamilton (1989) put forward an algorithm based on the discrete-state regime shifts in the Markov process. Hence this study also followed this approach and models herding using the Regime-Switching model.

Through formal testing, the study found three regimes in the Indian stock market by succeeding in the seminal work of Balcilar et al. (2013) and Fu and Wu (2021). Equation (2) is just extended by dividing the series into three regimes shifting across intercept and standard deviation as shown in equation 8. All the variables are varying across regimes except lags of the dependent variable.

$$CSAD_t = \gamma_{0,r_t} + \gamma_{1,r_t}\left|R_{m,t}\right| + \gamma_{2,r_t}\left(R_{m,t} - \overline{R}_m\right)^2 + \gamma_3 CSAD_{t-1} + \gamma_4 CSAD_{t-2} + \sigma_{r_t}\varepsilon_t \quad (8)$$

Here, $\in_t \sim N(0,1)$ is the innovation term and σ_{r_t} is the standard deviation, a measure of volatility. r_t is discrete regime variable can take the values $r_t = [0,1,2,\ldots\ldots\ldots,m]$ by following the three-state first-order Markov process. The Markov property is based on the transition probabilities which are constant across states and represented by the following specifications,

$$P\left(r_t = j\right) = p_{ij} \tag{9}$$

These transition probabilities with m number of regimes form a transition matrix of (m*m) regimes which is stated here as (Guo et al., 2011)

$$P = \left[p_{00}\, p_{01} \dots\dots\, p_{0m}\, p_{10}\, p_{11} \dots\dots\, p_{1m}\, p_{m0}\, p_{m1} \dots\dots\, p_{mm}\right] \tag{10}$$

$$\sum_{j=1}^{m} p_{ij} = 1 \text{ where } j = 0, 1, 2, \dots\dots, m \text{ and } 0 \le p_{ij} \le 1$$

Where pij is the constant transition probabilities in regime i at a time t+1 certain that the market was in regime j at t-1 time period. In the Markov model, expected duration is also calculated which states how many numbers of days, months, or years, the particular regime lasts for. It is calculated here as:

$$E\left(D_i\right) = \frac{1}{1-p_{ii}}\ ,\ i = 1, 2, 3 \dots\dots m \tag{11}$$

Where, E(Di) denotes the duration of regime i.

The estimation method used for the regime model is the maximum likelihood and robust standard error is calculated using Hessian and OPG matrix.

Hence using the Markov Regime-switching model, the current research has tested the following research questions in the Indian Equity market:

- **Procedure adopted for Time-Varying Measure**

1. Identified the total regimes through the likelihood ratio test and different model selection criteria.
2. Applied maximum likelihood estimation method and estimated different equations for different regimes.

3.2.1 Herd Behavior in Size-based Portfolio

This section highlights the testing methodology for identifying herding in different size-based portfolios. First of all, it is necessary to bifurcate the sample companies into size-based portfolios. The following steps are undertaken for bifurcation:

1. Following the methodology of Fama and French (1995), all sample companies have been divided into single sorted portfolios every year during the whole study period.
2. First of all, companies have been arranged in ascending order each year.
3. Median value has been calculated each year.
4. After that, those companies have been identified as large-capitalization companies whose market cap is above the median value, and those companies are identified as small-capitalization companies whose market cap is below the median value.
5. At the end of September each year, a thorough reorganization of the portfolio has been conducted.
6. Each year cross-sectional average returns have been calculated and herding variables like CSAD and market return are computed.

Hence following the above methodology, we have checked the research question as follows:

RQ 1: Does dynamic herd behavior differ between large-capitalization and small-capitalization stocks in the Indian stock market?

3.2.2 Herd Behavior in Volume-based Portfolio

This section highlights the investigation of herd behavior in the volume-based portfolio. To represent volume, every year at the end of each September, several shares traded were collected for all sample companies. The sample companies are divided into high and low-volume companies every year from 2009 to 2023 following Fama and French (1995). The steps for bifurcation are similar to size-based portfolios. Hence, we have addressed the following research question:

RQ 2 Does Dynamic Herd behavior differ in high- and low-volume-based portfolios in the Indian stock market?

3.2.3 Herd Behavior in value and growth stocks

This section highlights the investigation of herding in value and growth stocks. Value stocks are those whose shares are traded at a lower price than their fundamental value. These stocks have a low profit-to-book (PB) ratio, high dividend yield, and low price-to-earnings ratio. Growth stocks are those stocks traded at a higher price than their fundamental value. These stocks have a higher profit-to-book (PB) ratio, low dividend yield, and high price-to-earnings (PE) ratio. To analyze herding among value and growth stocks, we have taken the profit-to-book ratio as a criterion for the bifurcation of sample companies. Each year, the profit-to-book ratio for March is analyzed, and a portfolio is constructed at the end of September

The following steps are undertaken for portfolio formation:

1. To facilitate this process, the selected companies have been organized in ascending order of their profit-to-book ratios as of the end of September each year.

2. Then, the sample companies have been identified as value, neutral, and growth stocks but analysis were performed on value and growth stocks only. The top 30% PB ratio companies are termed as growth stocks, while the bottom 30% PB Ratio companies have been termed as value stocks, and the remaining stocks have been identified as neutral stocks.

3. The variables have been calculated for herding analysis.

RQ 3: Does Dynamic Herd Behavior exist in value and growth stocks in the Indian Stock Market?

4. Empirical Results and Analysis

This part explains the analysis of both linear and Regime-Switching models. First, we describe the variables' characteristics using some stylized facts on return and dispersion. The consequent section encompasses the findings of the Regime Switching model in different factor portfolios.

2.4.1 Stylized Facts

Table 1 explains the stylized facts of market return and cross-sectional absolute dispersion. The mean of CSAD (1.54 per cent) is higher than the market return (0.07 per cent), enabling higher variations in dispersion series than market returns. The standard deviation of the CSAD (0.36 per cent) is less than the market return (1.14 per cent), highlighting the volatility clustering in the dispersion series. Skewness is negative for market returns, indicating the high negative returns while the skewness is positive for CSAD. Moreover, the kurtosis is very high for both the series representing Fat-tails. Furthermore, the jarque-bera statistics are significant, showing a non-normal distribution. The stationarity test (Augmented Dickey-Fuller test) displays that the variables are stationary at level.

The Auto-correlation function at different lags for the CSAD series is significant. It conveys that the dispersion series is positively auto-correlated to higher levels of lags and shows signs of volatility clustering. The ACF of market returns is almost significant at higher lags, and there is no trend in the series. This means the market returns have a lower level of serial correlation with its previous values than the cross-sectional dispersion. These findings are in tune with various earlier studies that applied the Regime Switching models for fat-tails, volatility clustering, and higher serial correlation (Balcilar et al., 2013; Cont, 2010; Fu & Wu, 2021; Sen & Subramaniam, 2019; Singh & Singh, 2017).

Table 1 Stylized Facts

Statistics	CSAD	RM
Mean	1.54%	0.07%
Std.Dev.	0.36%	1.14%
Skewness	2.39	-1.10
Kurtosis	13.96	13.60
Observations	3531	3531
ADF Test	-7.802 ***	-19.86 ***
Jarque-Bera test	21055.95 ***	17275.15 ***
ACF1	0.785	0.159
ACF5	0.627	0.051
ACF20	0.421	-0.000

Source: The authors own computation using E-views 9.0
Notes: ***Significance at 1% level. Jarque-Bera is used to test normality in the series. ACF is the autocorrelation function up to n lags. The Augmented Dickey-Fuller (ADF) test assesses whether a time series is stationary.

2.4.4 Herding Results in Different Factor Portfolios

This study investigates the presence and dynamics of herding behavior in the Indian equity market using a Markov Regime-Switching Model across three volatility regimes—low, high, and extreme—during the period 2009 to 2023. The analysis focuses on different factor-based portfolios constructed using the Fama and French (1995) methodology, specifically portfolios based on market capitalization, trading volume, and Price-to-Book (P/B) ratios. The results indicate that herding behavior is not uniformly present across all portfolios and regimes, but rather is highly regime-dependent, with most herding concentrated in the extreme volatility regime. not attract the same level of attention or imitation, explaining the absence of herding in this segment. These findings are consistent with Chauhan et al. (2020), who observed herding behavior primarily in large-cap stocks in the Indian market, and Fu and Wu (2021), who attribute such behavior to the influence of institutional attention and media coverage.

Second, regarding Price-to-Book (P/B) ratio-based portfolios, the study finds evidence of herding in value stocks—those with low P/B ratios—during extreme volatility, whereas growth stocks with high P/B ratios do not exhibit herding behavior. This result implies that in times of extreme market stress, investors tend to move collectively into value stocks, possibly perceiving them as undervalued or offering safety through strong fundamentals. Value investors, in particular, often rely on similar fundamental signals such as book value and earnings, and during volatile periods, these signals become more pronounced. As these investors act in unison, either First, in the case of market capitalization-based portfolios, the study finds significant herding behavior in large-cap stocks during extreme volatility, whereas no herding is observed in small-cap stocks. This suggests that during periods of heightened uncertainty, investors tend to follow the actions of others more in large-cap stocks. A plausible explanation is that large-cap stocks receive more attention from institutional investors, analysts, and the media, making them more visible and perceived as relatively stable during turbulent times. This increased attention can lead to a cascading effect where investors mimic trades made by prominent market participants, resulting in herding behavior. In contrast, small-cap stocks typically suffer from lower liquidity, higher information asymmetry, and limited analyst coverage. As a result, they do due to similar strategies or shared analyst recommendations, others may follow, further amplifying the herding effect. On the other hand, growth stocks are usually characterized by higher valuations and expectations about future earnings, making them more volatile and less attractive in uncertain conditions. Investors may be more cautious or divergent in their decisions with these stocks, leading to an absence of herding. These observations align with the findings of Fu and Wu (2021), who noted that herding tends to be more pronounced in undervalued or less speculative stocks during volatile regimes.

Third, the study identifies strong herding behavior in high trading volume portfolios during extreme volatility, while low-volume portfolios show no such behavior. This finding highlights that investors are more likely to imitate others when trading in stocks with high liquidity and trading activity. High-volume stocks are often perceived as safer and easier to exit during uncertain times, attracting more attention from both retail and institutional investors. According to Lan and Lai (2011), liquidity plays a critical role in attracting investors seeking quick returns, especially during volatile periods. Furthermore, high trading volume may serve as a signal that other investors are acting on important information, prompting uninformed or momentum-driven investors to follow their lead, thus contributing to herding behavior. This contrasts with earlier Indian studies, such as those by Garg and Gulati (2013) and Lao and Singh (2011), which found no relationship between herding and trading volume using linear models. However, the current study's use of a nonlinear regime-switching framework allows for a more nuanced understanding of investor behavior under different market conditions, revealing that herding is indeed significant in high-volume stocks, particularly when market volatility is extreme. This finding also mirrors the conclusions of Fu and Wu (2021), who documented similar patterns in the Chinese equity market.

Overall, the study concludes that herding behavior among Indian investors is strongly regime-dependent and is most evident during extreme volatility conditions. Investors are more likely to follow each other when trading in large-cap stocks, value stocks, and high-volume stocks, likely due to greater visibility, analyst coverage, perceived safety, and liquidity. In contrast, small-cap stocks, growth stocks, and low-volume stocks exhibit no significant herding, suggesting more independent or less coordinated investor behavior in those segments. These insights have important implications for understanding investor psychology during market stress and can help both regulators and portfolio managers in designing policies and strategies to mitigate the adverse effects of irrational crowd behavior.

CONCLUDING OBSERVATIONS AND PRACTICAL OBSERVATIONS

Our study takes a deep dive into the dynamic nature of herd behavior in the Indian financial market for 2009-2023 using the Markov Regime model. Our study has examined investigated herding in different factor portfolios. We have employed Chang et al. (2000) base model for measuring uniformity among Indian investors. The regime model identifies the three regimes as high (Regime 0), low (regime 1), and extreme volatility regime (Regime 2), respectively. The findings of different factor portfolios have showed significant herding during high volatile regime in low pb ratio stocks (value stocks), high volume stocks, and large capitalization stocks during extremely volatile regimes. The outcomes of current research are useful for stakeholders and market controllers. The investors should form an appropriate strategy to readjust their market portfolio at the time of high volatility or not be captivated by the excess returns created by bubbles in extreme market situations. These results illustrate that the Indian market has become efficient with time as the market regulations continuously improve and information transmission become transparent. Hence, investors should make decisions based on the company's fundamentals, but during any uncertainty, they are exposed to high sentiments and follow each other. Investors need to construct larger portfolios at times of high volatility to maintain the same level of diversification (Chiang & Zheng, 2010; Fu & Wu, 2021). The findings of our study carry important implications for both market regulators and portfolio managers. For regulators, the evidence of significant herding behavior during periods of high and extreme volatility—particularly in value stocks (low price-to-book ratio), high-volume stocks, and large-cap stocks—signals the need for enhanced market oversight. Real-time monitoring tools should be strengthened to track these segments closely during turbulent periods, as herding can amplify market instability and contribute to the formation of price bubbles. Furthermore, regulators could consider implementing regime-sensitive circuit breakers or volatility controls to curb excessive market movements during times identified as high-risk. Strengthening disclosure requirements during such regimes may also help reduce information asymmetries that fuel herd behavior. In addition, investor education initiatives focusing on the dangers of following the crowd in volatile markets could help promote more rational decision-making among retail investors.

Table 2 Estimation Outcomes of Regime Switching Model in Factor-Based Portfolios (2-Class)

Coefficients	**Large Cap**	**Small Cap**	**High PB**	**Low PB**	**High Volume**	**Low Volume**
γ_{00}	0.006***	0.008***	0.006***	0.009***	0.007***	0.006***
γ_{01}	0.005***	0.006***	0.005***	0.007***	0.005***	0.005***
γ_{02}	0.006***	0.009***	0.008***	0.011***	0.006***	0.008***
γ_{10}	0.109***	0.124***	0.143***	0.153***	0.100***	0.129***
γ_{11}	0.089***	0.133***	0.155***	0.142***	0.083***	0.153***
γ_{12}	0.313***	0.184***	0.295***	0.255***	0.287***	0.222***
γ_{20}	1.597***	-0.420	1.154***	-0.917	0.672***	1.164***
γ_{21}	2.762**	1.113***	0.984***	-0.342	1.794***	0.637
γ_{22}	-0.942**	-0.218	-0.910	-0.864*	-0.927***	-0.425*
γ_{3}	0.352***	0.353***	0.334***	0.272***	0.360***	0.379***
γ_{4}	0.116***	0.121***	0.130***	0.115***	0.149***	0.116***
σ_{0}	0.0017***	0.002***	0.002***	0.002***	0.002***	0.018***
σ_{1}	0.0011***	0.001***	0.001***	0.001***	0.001***	0.013***
σ_{2}	0.003***	0.002***	0.004***	0.004***	0.004***	0.003***
P_{00}	0.92	0.97	0.96	0.95	0.93	0.96
P_{11}	0.95	0.98	0.95	0.97	0.97	0.97
P_{22}	0.83	0.98	0.95	0.91	0.70	0.97
N_{0}	1731	1369	1880	1725	1082	1669
N_{1}	1449	1818	1460	1580	2252	1579
N_{2}	349	342	189	224	195	281
N	3529	3529	3529	3529	3529	3529
τ_{0}	17.66	65	34.18	35.20	22.54	43.92
τ_{1}	27.34	113	31.06	42.70	64.34	47.85
τ_{2}	7.27	57	23.63	16	3.55	46.83
AIC	-9.768	-9.5911	-9.656	-9.162	-9.515	-9.857
LOG L	17256.99	16943.648	17058.039	16187.13	16810.62	17414.29
LR TEST	1026.5***	516.20**	788.60***	606.49***	818.25***	595.03***

Source: Authors' own computation using Ox-metrics 7.0

Notes: AIC is the information criterion. LOG L is log-likelihood. PB is the Market-to-Book Ratio. * Denotes significance at the 10% level, indicating moderate statistical evidence. ** Denotes significance at the level of 5%, reflecting a stronger level of statistical evidence. *** Denotes significance at the level of 1%, suggesting a very high level of statistical significance.

For portfolio managers, the dynamic nature of herding across regimes calls for more adaptive investment strategies. Integrating regime-switching models into portfolio construction and risk management processes can help managers adjust asset allocations in response to shifting market conditions. For example, given the observed tendency for herding in value and large-cap stocks during volatile periods, managers might reduce exposure to these segments or employ hedging strategies during such times. The findings also open up opportunities for contrarian investment approaches, where mispricings created by herd-driven behavior can be exploited. Additionally, behavioral indicators derived from herding dynamics can be incorporated into asset selection and timing strategies, enhancing overall portfolio performance. Ultimately, understanding the regime-dependent nature of herding behavior enables both regulators and market participants to respond more effectively to market risks and inefficiencies.

We only consider static transition probabilities in the study. Further research can be conducted by considering the impact of other exogenous variables like market sentiments or other global factors on herding through the time-varying transition probabilities regime model. Moreover, one can differentiate between different types of herding as we measured herding at market consensus.

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