



## Does Regime-Dependent Volatility Drive Dynamism in Investor Herding?

Komal Jindal<sup>a</sup> ✉, Meera Bamba<sup>b</sup>, Mamta Aggarwal<sup>c</sup>

<sup>a,c</sup>Department of Commerce, Indira Gandhi University, India

<sup>b</sup>Department of Commerce, Chaudhary Bansi Lal University, India

### Abstract

The existing literature on herding often uses the static model to test herd behaviour in the Indian market context. Hence, the objective of this paper is to investigate the dynamic herd behaviour for S&P BSE 500 from 2009-2023 using the Markov Regime Switching model. Results exhibit the occurrence of three regimes, namely, high, low, and extremely volatile regimes. Findings suggest that the Indian market moves into the order of low, high, and extreme volatility (LHC), similar to other developed countries. This has implications for investors to either exit from the market or reframe their portfolio through hedging techniques before the market enters into extreme volatility. Moreover, the results exhibit anti-herding in high and low-volatile regimes. Our study discloses the presence of herding in crashes or extremely volatile regimes, showing that Indian investors start following each other during crash-like situations. This research is significant for individual investors, portfolio managers, and stock market regulators.

**Keywords:** Dynamic Herding, Indian Equity Market, Three Regime-Switching Model, Volatility Regime, Markov Model

Received:  
28 August 2023

Accepted revised version:  
11 March 2024


Published:  
30 June 2024

Suggested citation: Jindal, K., Bamba, M. & Aggarwal, M. (2024). Does regime-dependent volatility drive dynamism in investor herding? *Colombo Business Journal*, 15(1), 54-79.

DOI: <https://doi.org/10.4038/cbj.v15i1.169>

© 2024 The Authors. This work is licensed under a [Creative Commons Attribution 4.0 International License](https://creativecommons.org/licenses/by/4.0/) which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

✉ [komal.comm.rs@igu.ac.in](mailto:komal.comm.rs@igu.ac.in)

 <https://orcid.org/0000-0001-9544-2722>

## **Introduction**

The most common type of bias in the financial market is herd instinct or herd behaviour. In general terms, herding means following other investors with superior information while suppressing their beliefs. Many causes behind herd behaviour can be deduced from the theoretical literature. As many previous studies have explained, herding can arise due to reputational concerns, informational cascade effect, superiority of information, and a complex informative structure environment (Avery & Zemsky, 1998; Bikhchandani et al., 1992; Scharfstein & Stein, 1990). Moreover, these types of behavioural biases can cause volatility to be high and extreme market situations in the equity market (Litimi, 2017). Analysing herding is very important because it can cause high volatility in the market, enlarging the gap between the market price and fundamental price of any stock and creating a bubble-like situation in the stock market (Bikhchandani et al., 1992; Chiang & Zheng, 2010). This encourages the investors to make correct decisions, resulting in an efficient market. An understanding of herd behaviour enables better investment decisions with portfolio diversification. With this objective, we investigate herding in the Indian stock market. There are multiple reasons for choosing the Indian stock market. First, emerging economies like India have the presence of herding due to cultural differences, incomplete enforcement laws, and uneducated and uninformed investors (Chang et al., 2000; Kanojia et al., 2022; Lao & Singh, 2011). Second, India is the fastest-growing economy in emerging markets, with more relaxed regulations related to foreign capital. This, in turn, led to an enormous flow of foreign institutional investment in India. So, it is observed that during extreme market situations, investors start following Foreign Institutional Investors (FIIs) and move in the same direction.

This research adds multiple insights into the herding literature. First, the existing study applies the Regime Switching constant probability model with three Markov states for the Indian stock market in which herd behaviour may or may not exist. In the case of volatile situations, the investors have become risk averse and start following the market trend to avoid excess risk. However, other types of investors exploit the benefits of an extremely volatile market by earning higher excess returns. Hence, it might be possible that investors react differently in various volatile situations. So, it is highly important to address the dynamic herding along with dynamic volatility. Herding can also be addressed through other linear models like structural break or Autoregressive Moving Average (ARMA) models. However, we have chosen the regime model to identify the hidden Markov states as it divides the market into multiple regimes based on the stochastic process. This model easily captures the dynamic pattern of complex time-series data (Shakya et al., 2017). The

three-regime model enables us to investigate the dynamic nature of cross-sectional dispersion and how structural breaks or events move the series into different regimes or states where herd behaviour can be observed (Balcilar et al., 2013). This is because linear models cannot capture the time-varying properties of any non-linear series (Chauhan et al., 2020; Choi & Yoon, 2020; Garg & Gulati, 2013; Lao & Singh, 2011). Second, less research has considered the significant autocorrelation property of cross-sectional absolute deviation in time-varying models, and this study includes two lag terms of explained variables in the Regime Switching model. Third, we establish the role of volatility in driving the dynamic herding in the Indian financial market.

The present study examines herding using both linear and non-linear models. First, the results are calculated through a linear herding model. Then, the non-linearity is tested in the financial time series, and several regimes are identified. After that, the Markov Regime Switching model is applied to investigate the dynamic herding in multiple regimes. We identified the existence of three regimes in the Indian market with high, low, and extreme volatility. Here, an extremely volatile regime means changing prices suddenly or abruptly by moving the series to a very high or very low. However, there is a bidirectional shifting of high and extreme volatile regimes, identical to the study of Balcilar and Demirer (2015), motivating the market regulators to make a mechanism to stop the market transitions from high to extreme volatile regimes.

The paper is ordered as follows: Section 2 contains the related studies. The data and empirical framework are presented in Section 3. Section 4 examines the results and analysis, and Section 5 presents the conclusion and implications of the study.

## **Literature Review**

### ***Theoretical Background***

Many previous studies have examined the concept of herding and the factors that can lead to a herd-like situation in the stock market (Avery & Zemsky, 1998; Bikhchandani et al., 1992; Spyrou, 2013; Wermers, 1999). Furthermore, Herding is an irrational behaviour that persuades investors to make decisions based on others' information. Market participants can cause herding for various reasons; for example, managers do herding out of reputational concern (Scharfstein & Stein, 1990). They present a learning model where the labour market can update the understanding of managers' abilities due to their investment decisions. This behaviour may be socially inefficient but is rational from the managers' standpoint. Likewise, Bikhchandani et al. (1992) exhibit an informational cascade as the cause behind local conformity and

the fragility of mass behaviour. An informational cascade occurs when it is optimal for the individual to observe the actions of others while ignoring their private information. However, it can soon be fragile when new information arrives in the market. In their theoretical model, Avery and Zemsky (1998) explain that herding behaviour is not possible in the long run in a simple informational structural environment. However, the more complex informative structure can lead to herd behaviour and the creation of a price bubble in the short run in the case of multidimensional uncertainty. Literature suggests two types of herding, which investors can reflect on. One is rational herding, and another is irrational herding. Rational herding is unintentional or spurious based on the fundamental information available to all (Bikhchandani & Sharma, 2000; Galariotis et al., 2015). Irrational herding is intentional and based on information unavailability (Shiller et al., 1984; Trueman, 1994).

### ***Herding in the Financial Market***

Earlier empirical studies have primarily relied on two strands of methodology to measure herd behaviour. Lakonishok et al. (1992) has checked out the impact of institutional trading on stock prices. As an institutional trader, they have taken the trading of money managers to measure herding in the equity funds. Their model is based explicitly on the buying and selling order of money managers for a particular stock in a quarter. The other technique that measures flocking toward market consensus using the famous Cross-Sectional Standard Deviation (CSSD) and Cross-Sectional Absolute Deviation (CSAD) was proposed and modified by Chang et al. (2000) and Christie and Huang (1995), respectively. Many empirical studies employ the CSSD to assess the herding. Tan et al. (2008) applies the linear model in the Chinese market and observes significant herding. Chiang and Zheng (2010) explore uniformity at the global level using CSAD, showing important herding in advanced stock markets and Asian markets. Rompotis (2018) checks the uniformity in exchange-traded funds with the help of a linear model and exhibited no herding in Exchange-Traded Funds (ETFs). Choi and Yoon (2020) study uniformity in the Korean equity market using a cross-sectional absolute deviation approach and find herding behaviour during down market returns. Moreover, some studies also investigate herding during or after the outbreak of COVID-19. Nguyen and Vo (2023) examine the herding in the Vietnamese stock market during and after the pandemic. Results reveal the existence of herd behaviour during and after the pandemic, stating that these crisis-like situations exacerbate the similarity in the financial market. Likewise, recently published Tauseef (2023) studies herd behaviour in the Pakistan

stock market during the financial crisis and COVID-19. They report significant herding during the COVID-19 period and the financial crisis. Ferreruela and Mallor (2021) describe herding before and after the global financial crisis but no herding during the pandemic. They also observe significant evidence of herding during the pandemic but during the time-high volatile periods only.

Later, the studies on herding shift their analysis to more advanced econometric models to identify the time-varying nature of herding. Hwang and Salmon (2004) first propose a model measuring dynamic herding that relies on monthly betas using Kalman filter's state-space model. Similarly, Arjoon and Bhatnagar (2017) study herding behaviour in Frontier markets. They examine both static and dynamic herding, as well as herding during times of volatility. To analyse time-varying herding, they utilise a state-space model. Their findings suggest that herding evolves as the behaviour of investors changes with fluctuations in information flow. Recently published Yang and Chuang (2023) examine dynamic herding in highly volatile US, Taiwan, and China markets. They have applied the Kalman filter model and the GARCH model for analysis. Results explain the similarity among the market investors in volatile periods during the financial crisis but low herding during the pandemic. From the above studies, it can be observed that researchers have shifted their interest toward dynamic herd behaviour. Schmitt and Westerhoff (2017) have clearly stated that a speculator's herd behaviour increases the volatility clustering in the market using the agent-based market model. Blasco et al. (2012) check out the impact of herding on volatility in the Spanish stock market. Results indicate the presence of a linear relationship between herding and volatility. Likewise, Fei and Liu (2021) also analyse the role of herding in stimulating volatility in the Chinese stock market. Findings exhibit that herding can stimulate volatility but to a different degree. The above-stated studies on herding and volatility signify a significant relationship between volatility and herding. Hence, the present study chooses to investigate the role of herding with particular reference to volatility in the Indian stock market. Herding is generally a short-lived phenomenon prominent in extreme market situations, which is measured by using daily or intraday data (Gleason et al., 2004). Hence, by considering the short-term presence of herding, Klein (2013) explains the dynamic herding using the Markov Switching SUR model and reveal herd behaviour during high volatility. Several empirical studies use a regime-switching model with two or three regimes to address the herding impact. Balcilar et al. (2013) propose a three-regime Markov model and tested the herd mentality in the Gulf Arab Stock Market. They show herd behaviour in the Crash regime. Balcilar and Demirer (2015) investigate the herding in Borsa Istanbul by applying the dynamic

transition probability Regime-Switching model. They arrive at the same result of herding in extreme/highly volatile regimes, consistent with previous studies. Similarly, using the Regime-Switching model, Babalos et al. (2015) check dynamic herding in the US Real estate market. They imply significant herding in the crash regime and the evidence of negative herding in low/high volatility. Likewise, Kabir and Shakur (2018) investigate herding in various international markets using a smooth transition regression model. Their study indicated that most countries, including India, herd in highly volatile regimes. Akinsomi et al. (2018) examine herd behaviour in the real estate investment trust in the UK. They divide the market into three regimes: low, high, and extreme volatile periods. They find no herding using the static model and exhibit significant herding in the low volatile periods compared to anti-herding in high volatile periods. Fu and Wu (2021) investigate the herd mentality among Chinese market investors and find that herding is regime-dependent in high-volatile regimes. Similarly, Ah Mand and Sifat (2021) establish evidence of prominent herding in high-volatile regimes in Bursa Malaysia. Javaira et al. (2023) establish a relationship between volatility and dynamic herding in the energy sector during COVID 19. They find that herding is significantly affected by three volatility measures: global volatility, oil market volatility, and pandemic volatility.

### ***Indian-Specific Evidence on Herding***

Many studies related to herding have also been conducted in the Indian financial market. Lao and Singh (2011) discover a herd-like situation in the Indian financial market during market uncertainty using the CSAD static model from 1999-2009. Similarly, Garg examine uniform behaviour in normal and extreme market conditions from 2000-2013. The results convey the message that no imitation by investors in either type of situation. A study by Poshakwale and Mandal (2014) investigate herd mentality using the Kalman filter in the National Stock Exchange of India. They exhibit that herding increased due to market volatility after allowing time-varying variables. Kumar et al. (2016) document no uniformity among the Indian market participants in both normal and uncertain market situations for 2008-2015. Ganesh et al. (2017) investigate the uniform behaviour in the Indian bourses for 2005-2015 and find evidence of no herding overall except in 2011 and 2014. Ansari and Ansari (2021) have recently measured herding for 2007-2018 using the static model in normal and bull/bear phases. Their findings show the anti-herding among Indian market participants in all market conditions. Similarly, Kanojia et al. (2022) exhibit no herding for the Indian market using the CSAD methodology for the period 2009-2018. The evidence depict no herding in any market conditions. Shrotryia and Kalra

(2022) have studied herding in Brazil, Russia, India, China and South Africa (BRICS) using a quantile regression approach. The evidence of their study discloses anti-herding in the Indian financial market.

### ***Research Gap***

From the above discussion, it is discovered that literature on Indian herding has shown evidence of no herding or anti-herding in the Indian stock market. Still, some studies show that herding may be present during crisis periods. All studies have used the static approach to measure herding by skewing towards analysing herding in up/down market conditions. Although the regulations regarding investment have been considerably improving after liberalisation in the Indian stock market. However, India is still an emerging country with more small retail investors who behave irrationally in extreme market situations (Ansari & Ansari, 2021). Moreover, the Indian stock market has involved the greater entry of foreign institutional investors in the recent decade, making the Indian market vulnerable to various investor sentiments like herd behaviour and positive feedback trading (Mukherjee & Tiwari, 2022). Furthermore, various unprecedented events like COVID-19 increased the inefficiency in the Indian stock market (Bhatia, 2022). Domestic investors started following the foreign investors in a similar manner. All these reasons mentioned above make the study interesting to explore whether, with time, herding behaviour has evolved or vanished in the Indian market. Our study differs from the recent study of Ansari and Ansari (2021) in several ways. First, they test herding in the up/down market, but we have analysed flocking with particular reference to volatility. Second, they have used a static model to measure the herding., We explore the dynamic nature of herding in a three-regime specification. The study of Poshakwale and Mandal (2014) investigate herd mentality using the Kalman filter in the National Stock Exchange of India. They rely on monthly beta rather than daily or intraday. Kabir and Shakur (2018) explore uniformity in high- and low-volatile regimes in multiple countries, including India, using the smooth transition model. However, our study differs from their methodological framework as we incorporate a three-regime specification using the Markov regime-switching model. As many previous studies indicate, the Markov regime switching model provides more flexibility with the point of time as compared to other non-linear models like GARCH or Kalman filter (Akinsomi et al., 2018; Babalos et al., 2015; Balcilar & Demirer, 2015; Fu & Wu, 2021; Kabir & Shakur, 2018; Mand & Sifat, 2021). It is suitable for the time series, the behaviour of which is not permanent, but reverts repeatedly. The Markov regime switching model captures even a tiny shift in a series and estimates time-varying coefficients more accurately. Hence, there is a trend that various studies shifted their

focus towards the Markov regime switching models over time. Moreover, the results of past studies depict that CSAD has properties of regime-switching. To the best of our knowledge, no research in India has explored dynamic herd behaviour in the Indian market context using the Markov-Regime Switching framework. Against this backdrop, the objective of the present study is to assess the presence or absence of dynamic herd behaviour in the Indian stock market using the Markov regime switching Model.

## **Data and Econometric Framework**

### ***Data***

Data comprises daily stock-adjusted closing prices of individual stocks listed in S&P BSE 500 for 1/01/2009 to 31/03/2023 in the Indian equity market. Daily data can be considered high-frequency data in some contexts because it provides more precision than weekly or monthly data (Hung, 2019; Jebran & Iqbal, 2016). Information is lost in weekly or monthly data because it averages out the daily effect. Although many studies have considered intraday data as high-frequency data due to time and data availability constraints, we have taken daily data as the next best alternative to high-frequency data, which can depict volatility more clearly than other low-frequency data. Data has been collected using the Prowess IQ database from CMIE (Centre for Monitoring Indian Economy). We selected the study period from 2009 because, before that period, more than 50% of companies were excluded from the study 500 due to a high number of missing observations. First, those companies registered after the 1<sup>st</sup> of January 2009, are excluded from the study to match the number of observations of all companies. Later, the companies with missing data up to 10% of the total number of observations during the period are replaced using the linear interpolation method (Mertler et al., 2021). The total number of observations is 3531, and sample companies included in the analysis are 338 out of 500. After screening and cleaning the data, the cross-sectional individual and market returns are calculated. We have calculated our market return proxy by giving equal weights to each stock in the portfolio, as also calculated by many numbers of studies (Chang et al., 2000; Chiang & Zheng, 2010; Garg & Gulati, 2013; Kanojia et al., 2022). As such, we have not used value-weighted returns in CSAD calculation. For applying Markov Regime Switching models, it is necessary to test whether financial time series have a regime-switching framework or not. Hence, we applied the Linearity likelihood ratio, and Davies tests to check the same. Lastly, the results are calculated using the Regime and Static models. The analysis work has been performed using Ox-metrics 7.0.



### ***Econometric Framework***

This section explains the models used for the analysis work. Specifically, we started with the calculation of stylised facts of the variables used in the study. It provides the direction in which time series variables are going on. Next, for analysing the herding, the baseline model of Chang et al. (2000) is used. As the presence of structural breaks in high-frequency time series data and after finding the evidence of fat-tail, volatility clustering, and non-normal distribution in the studied variable, it is necessary to address these issues aptly. Hence, the appropriate regime-switching model is used to address these issues and analyse dynamic herding. However, before applying this model, we checked for non-linearity in the model through the likelihood ratio test and Davies upper bound test. Next, various information criteria are used to know the exact number of regimes. Lastly, the regime model specification is applied to measure time-varying herding in multiple regimes with the exact number of regimes to be known.

### ***Static Model***

The model to measure herd behaviour is CSSD, introduced by Christie and Huang (1995), and CSAD, improved by Chang et al. (2000). The methodology relies on the conditional Capital Asset Pricing model which describes the association of firm-level dispersion and the absolute market return is positive and linear. This relationship becomes negative and non-linear if herding occurs in the financial market.

The Firm return dispersion is calculated as follows:

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

Here, N is the total number of sample companies included in the study and  $R_{i,t}$  is the returns of individual stock on a day t.  $R_{m,t}$  is the equally weighted average market returns of all sample companies on a day t.

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

The negative and significant value of  $\gamma_2$  represents the herd behaviour. The idea behind the CCK (Chang, Cheng, and Khorana) model is that absolute market return and dispersion have a positive and linear relationship. Due to the presence of herd behaviour, this relationship becomes non-linear and negative. Investors start acting similarly while purchasing stocks, and the returns of stocks gather around the market return, leading the dispersion series to decrease or increase at a decreasing rate. The presence of absolute and squared market returns in the same model leads to high multicollinearity, which becomes a problem in the OLS models. Hence, to remove the multicollinearity, we follow the study of Yao et al. (2014), which deducts the

mean of market return from the squared market return to remove multicollinearity. Moreover, the study incorporates the two-lag term of the dispersion variable in the model to address the strong autocorrelation quality of dispersion. The study includes only two lag terms because higher-order lag does not improve the results (Lao & Singh, 2011). Many empirical studies included the lag term in their model to remove the autocorrelation. The study uses the heteroscedasticity and autocorrelation consistent standard errors of Newey and West (1987) and adds the lag term of the dependent variable to obtain the regression coefficients.

### *Regime Switching Framework*

The behaviour of many financial time series may change over time permanently (known as structural breaks), or may shift from one type to another type and revert (known as regime shifts). The regimes here are unobservable. One of the most widely used methodologies to model this type of non-linearity is Markov Regime-Switching model (Brooks, 2008) in which, regime-switching may occur at the error term's mean and standard deviation. Hamilton (1989) proposed an algorithm based on the discrete-state regime shifts in the Markov process., This study also follow the same approach and models herding using the Regime-Switching model.

Through formal testing, the study found three regimes in the Indian market by following the seminal work of Balcilar et al. (2013) and Fu and Wu (2021). Equation (2) is extended by dividing the series into three regimes shifting across intercept and standard deviation, as shown in equation (3). All the variables vary across regimes except lags of the dependent variable.

$$CSAD_t = \gamma_{0,r_t} + \gamma_{1,r_t}|R_{m,t}| + \gamma_{2,r_t}(R_{m,t} - \overline{R_m})^2 + \gamma_3 CSAD_{t-1} + \gamma_4 CSAD_{t-2} + \sigma_{r_t} \varepsilon_t \quad (3)$$

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

$$P(r_{t+1} = i | r_t = j) = p_{ij} \quad (4)$$

with

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

where  $p_{ij}$  is the constant transition probabilities in regime  $i$  at a time  $t+1$ . The estimation method used for the regime switching model is the maximum likelihood, and robust standard error is calculated using Hessian and OPG matrices. The study used Excel, E-views 9.0, and Ox-metric 7.0 statistical software for the analysis.

## Empirical Results and Discussion

This part explains the analysis of both linear and Regime-Switching models. First, we describe the variables' characteristics using stylised facts on return and dispersion. After that, results of both linear and Regime Switching models are shown with non-linear testing of the time series before applying the switching model.

### *Stylised Facts*

Table 1 explains the stylised facts of market return and cross-sectional dispersion. The mean of CSAD (1.54%) is more significant than the market return (0.07%), suggesting higher variations in dispersion series than market returns. The standard deviation of the CSAD (0.36%) is less than the market return (1.14%), 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 Augmented Dickey-fuller test is performed on intercept only to check the stationarity of the data. The stationarity test (Augmented Dickey-Fuller test) shows that the variables are stationary at level.

**Table 1: Stylised Facts**

Statistics	CSAD	R <sub>m</sub>
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

Notes: 1. \*\*\*  $p < 0.01$ . Jarque-Bera is for testing normality in the series.

2. ACF is the autocorrelation function up to  $n$  lags. ADF is the Augmented Dickey-Fuller test to check stationarity.

The Auto-correlation function at different lags for the CSAD series is significant. It implies 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 the series has no trend. This means the market returns have a lower serial correlation with their 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).

### *Results of Herd Behaviour in Static Model*

Here, Table 2 (second column) reports the estimates of the linear OLS (Ordinary Least Square) model put forth by Chang et al. (2000). First of all, the outcomes of the static model from Equation (2) state that the coefficient  $\gamma_2$  that measures the herd behaviour is insignificantly positive, showing the absence of herding in the overall market in the Indian market when linear OLS regression is used.

**Table 2: Estimation Results of Static and Markov Three Regime Switching Model**

Coefficients	Static Model Result	Regime Model Result
$\gamma_{00}$	0.003 (0.0002) ***	0.006 (0.0003) ***
$\gamma_{01}$	NA	0.004 (0.0002) ***
$\gamma_{02}$	NA	0.005 (0.0004) ***
$\gamma_{10}$	0.151 (0.0158) ***	0.081 (0.025) ***
$\gamma_{11}$	NA	0.107 (0.0080) ***
$\gamma_{12}$	NA	0.227 (0.0369) ***
$\gamma_{20}$	0.379 (0.4652)	2.516 (0.2320) ***
$\gamma_{21}$	NA	1.450 (0.190) ***
$\gamma_{22}$	NA	-0.529 (0.2861) *
$\gamma_3$	0.503 (0.0204) ***	0.443 (0.0191) ***
$\gamma_4$	0.197 (0.020) ***	0.147 (0.0168) ***
$\sigma_0$	0.0018***	0.0017 (0.000) ***
$R^2$	0.75	NA
$\sigma_1$	NA	0.0012 (0.000) ***
$\sigma_2$	NA	0.0036 (0.0001) ***
$P_{00}$	NA	0.95
$P_{11}$	NA	0.97
$P_{22}$	NA	0.74 (Contd.)

Coefficients	Static Model Result	Regime Model Result
N <sub>0</sub>	NA	806
N <sub>1</sub>	NA	2473
N <sub>2</sub>	NA	250
N	3529	3529
τ <sub>0</sub>	NA	29.85
τ <sub>1</sub>	NA	41.92
τ <sub>2</sub>	NA	4.31
AIC	-9.778	-10.022
LOG L	17258.58	17704.55
LR test	-	891.94***
Davies test	-	0.000***

- Notes: 1. The table reports the result of two models i.e., Static model:  $CSAD_t = \gamma_0 + \gamma_1 |R_{m,t}| + \gamma_2 (R_{m,t} - \bar{R}_m)^2 + \gamma_3 CSAD_{t-1} + \gamma_4 CSAD_{t-2} + \varepsilon_t$ . Regime-Switching model :  $CSAD_t = \gamma_{0,r_t} + \gamma_{1,r_t} |R_{m,t}| + \gamma_{2,r_t} (R_{m,t} - \bar{R}_m)^2 + \gamma_3 CSAD_{t-1} + \gamma_4 CSAD_{t-2} + \sigma_{r_t} \varepsilon_t$
2. Standard error is shown in parenthesis. The standard errors of the linear model are estimated using Newey and West HAC standard errors.
3. For the regime model, robust-standard errors are calculated with the BFGS Algorithm.
4. AIC is the Akaike information criterion.
5. Log L is the log-likelihood of the model. LR is the likelihood ratio test with their respective  $p$ -values and Davies test  $p$ -values.
6. \* $p < 0.1$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$ .

Many previous Indian research studies find similar results of no herding at the overall market level using the static model (Garg & Gulati, 2013; Kanojia et al., 2022; Lao & Singh, 2011). However, it is possible that these studies did not detect herding using a static model due to the time-varying nature of the return dispersion series. Moreover, both lag term coefficients are significant, which supports using two lagged values of the dependent variable to overcome the autocorrelation problem in the return dispersion series (Benkraiem et al., 2021; Yao et al., 2014). The study has also calculated the results by incorporating three lags of the dependent variable in Equation (2). However, the results do not improve much; hence, only two lag terms are included in the static model.

### **Results of Herd Behaviour in the Regime Switching Model**

Before selecting the regime switching model for dispersion series, it is essential to identify the non-linearity in the time series. It is better to know before testing whether the regime switching model is a superior fit to the data. To check the non-linearity, by referring to Babalos et al. (2015) and Balcilar et al. (2013), the present study has calculated the standard likelihood ratio test statistic using log-likelihood

values which follows  $\chi^2$  distribution with  $q$  degree of freedom of regimes. However, in the Markov Regime Switching model, unidentified nuisance parameters exist under the null hypothesis (Brooks, 2008), and therefore, standard distribution does not apply to it. Hence, we also reported the  $p$ -values calculated using the approximate upper bound test proposed by Davies (1987).

Table 3 depicts the rejection of the static model at a 1% level of significance in favour of the regime-switching model. It means that the dispersion series is non-linear and has the presence of multiple regimes. Moreover, in deciding the exact number of regimes, the LR and Davies test strongly reject two regime-switching models against a three-regime- model at a 1% level of significance.

**Table 3: Likelihood Ratio Test for Different Models**

<b>H<sub>0</sub>: static</b> <b>H<sub>1</sub>: MS (2)</b>	<b>H<sub>0</sub>: static</b> <b>H<sub>1</sub>: MS (3)</b>	<b>H<sub>0</sub>: MS (2)</b> <b>H<sub>1</sub>: MS (3)</b>
703.96***	891.94***	187.98***
(0.000) [0.000]	(0.000) [0.000]	(0.000) [0.000]

- Notes: 1. Static model shows OLS regression using Equation (2).  
 2. MS (s) is the regime-dependent intercept variance model with  $r$  number of regimes.  
 3. \*\*\*  $p < 0.01$ .  
 4. Linearity Likelihood ratio test is used to calculate test statistics.  
 5. The chi-square  $p$ -values are reported in parenthesis along with the  $p$ -values of Davies (1987) in square brackets.

Table 4 shows the log-likelihood and Akaike information criteria of the various estimated models with multiple regimes. It is clearly shown in the Table that the highest log likelihood is of the three-regime model, along with the lowest Akaike Information criteria. From the above criteria and formal tests, the study found that three regime models fit the study.

**Table 4: Best-Fitted Model Measures**

	<b>Linear</b>	<b>MS (2)</b>	<b>MS (3)</b>
Log Likelihood	17258.58	17610.56	17704.55
AIC	-9.778	-9.973	-10.022

- Notes: 1. AIC shows Akaike information criteria.  
 2. The static model shows OLS regression using Equation (2).  
 3. MS is the regime-dependent variance model for 2 and 3 regimes in Equation (3).

Studies have stated that the Markov model is more suitable for explaining dynamic herding and its various states (Balcilar et al., 2013; Mand & Sifat, 2021). Moreover, there are studies in the past that extend the CSAD approach in the Regime framework and explain the non-linearity in the CSAD model in both developed and emerging economies (Akinsomi et al., 2018; Babalos et al., 2015; Balcilar et al., 2013; Mand & Sifat, 2021)., The results of our study also exhibit the presence of different regimes in the CSAD model, and the information criteria are lower for the regime model than the static model. Hence, the study has applied the regime specification for modeling non-linear properties of herding specification and calculating the time-varying herding parameter along with regime switching.

Table 2 (third column) discloses the results of the Regime Switching model. To avoid overfitting variables and have parsimony in the model, this study assumes that serial correlation is regime-independent, similar to Fu and Wu (2021). For identification of regimes into high, low, and extreme volatility, the study closely examines the standard deviation of the error term represented by  $\sigma_{r_t}$ . Standard deviation of Regime 2 (0.0036) is exceptionally high as compared to high volatility regime 0 (0.0017) and low volatility regime 1 (0.0012).

The main coefficients of interest that measure herding in the Regime Switching model are  $\gamma_{20}$ (Regime 0),  $\gamma_{21}$ (Regime 1) and  $\gamma_{22}$  (Regime 2). The coefficients  $\gamma_{20}$  and  $\gamma_{21}$  are positively significant in high and low volatile regimes, respectively, implying negative herding in the Indian financial market. It means that Indian market participants make rational decisions when the market is highly volatile and stable. The possible reason for the negative herding is the ‘flight-to-quality’ or ‘overconfidence’ of investors during an unstable market (Ansari & Ansari, 2021; Gebka & Wohar, 2013). Lastly,  $\gamma_{22}$  is negative and significant in extreme volatile or crash regime 2, indicating that the investors are imitating each other when market is extremely volatile or in crash-like situations due to some unprecedented events. It may be because investors follow institutional investors to avoid extreme losses in extreme or crash regimes. The result of significant herding during extreme or crash regimes is in line with the findings of Balcilar and Demirel (2015) and Balcilar et al. (2013), which show herding during extremely volatile regimes in Borsa Istanbul and GCC markets. Moreover, the extremely volatile regime has 250 observations of the total number of observations, showing that three regime specifications fit the study. As residual diagnostics, we consider log Likelihood, Akaike Information criteria, the Portmanteau test, and the ARCH test for testing heteroscedasticity and autocorrelation. Table 4 shows that the regime model has a higher log-likelihood and lower AIC than the static model.

**Table 5: Residual Diagnostic for Scaled Residuals**

Scaled Residuals	Distribution	Statistics	<i>p</i> -value
Normality	Chi (2)	13.827	0.0022
Asymptotic normality	Chi (2)	12.266	0.0010
ARCH (1-1 test)	F (1,3507)	2.057	0.1516
Portmanteau (26)-squared scaled residuals	Chi (26)	26.708	0.4247

Moreover, Table 5 shows that the coefficient of the ARCH 1-1 test is insignificant, depicting no conditional heteroscedasticity in the fitted model.<sup>1</sup> The insignificant Portmanteau test statistic indicates the absence of any dependence structure or autocorrelation in the residuals, suggesting that the model is correctly specified.

### *Persistence of Market Regimes*

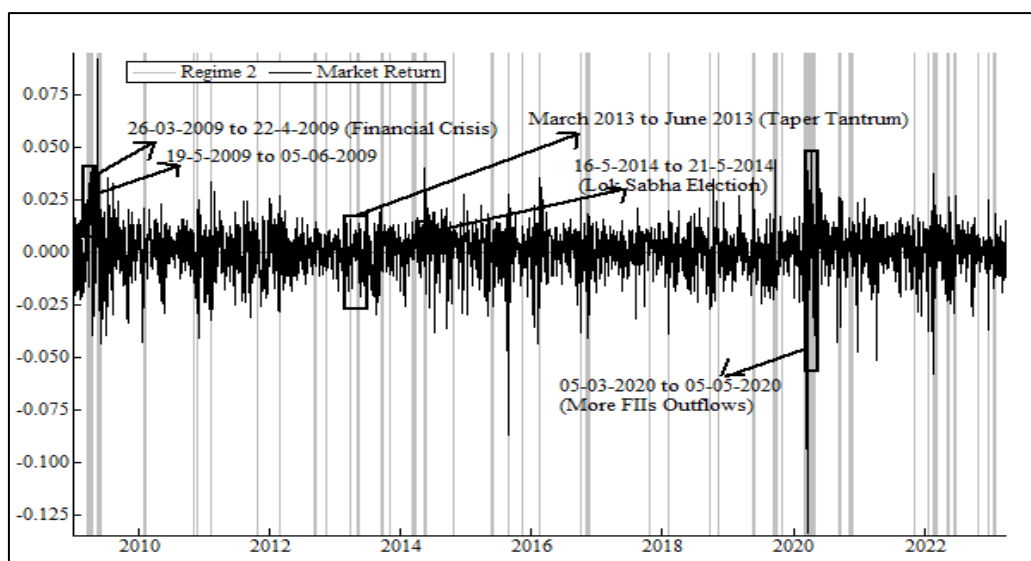
It is equally important to look at other essential features of Markov Switching-model such as transition probabilities ( $p_{ij}$ ) and smoothed probabilities for fitting the Regime Switching model to the data. Initially, the market is in regime  $j$  at time  $t$  and Table 2 shows the transition probabilities ( $P_{00}$ ,  $P_{11}$  and  $P_{22}$ ) of remaining in regime  $j$  at time  $t+1$ . The probability here suggests that the decoded regimes are stable and will remain persistent within the existing regimes. The high volatile regime 0 has 22.84 % number of observations compared to a low volatile regime with 70.08 % observations. However, the transition probability of a low volatile regime is 0.97 compared to the other two regimes, showing the high persistence of a low volatile regime. Moreover, the extreme volatile regime and high volatile regime transition probabilities are 0.749 and 0.95, respectively, depicting the validity of regimes. The mean duration of a low volatile regime is 41.92 days, implying that Regime 1 will last approximately 42 days. While the high volatile regime lasts 29.85 days, it implies that Regime 0 will last about 30 days. The average duration of extreme volatile regime is 4.31 days, indicating Regime 2 will last approximately four days. This depicts that

<sup>1</sup> We also conducted robustness checks to ensure the presence of Three-Regime specification and accuracy of the results. First, analysis was done from the Period 2010-2023 and then from 2012-2023. The results of both time periods show significant evidence of herding in Extreme or crash volatile regime with three regimes. ARCH 1-1 test null hypothesis is accepted at 1% significance level. Moreover, we also calculated the herding by assuming the switching in variance and other variables except the constant term. The results are similar to the fitted Markov intercept and variance regime switching model showing the presence of herding in the extreme volatile regime. However, the model is not a best fit so we applied the intercept and variance regime switch model. Results are not shown here to conserve space.



the low volatile regime is highly persistent compared to other regimes, similar to the findings of Balcilar et al. (2013). Figure 1 shows the period when significant herding was observed in the market. Although there are many instances of herding in the whole sample period, the long-lasting ones are as follows: The first most extended extreme volatility regime was from 26-03-2009 to 22-04-2009 (16 days), and then the market switched to high volatility. Then again, in Regime 2, the long-lasting regime is from 19-05-2009 to 05-06-2009, which is for 14 days, followed by the highly volatile regime. It means the Indian market has volatility clustering after the crash or extremely volatile regime in 2009. This outcome can be confirmed by the Ali and Afzal (2012), which also found volatility clustering in the Indian and Pakistan Equity markets during the crisis and a more substantial negative impact on the Indian stock market.

**Figure 1: Market Returns Showing Significant Herding in Extreme Volatile Regime**



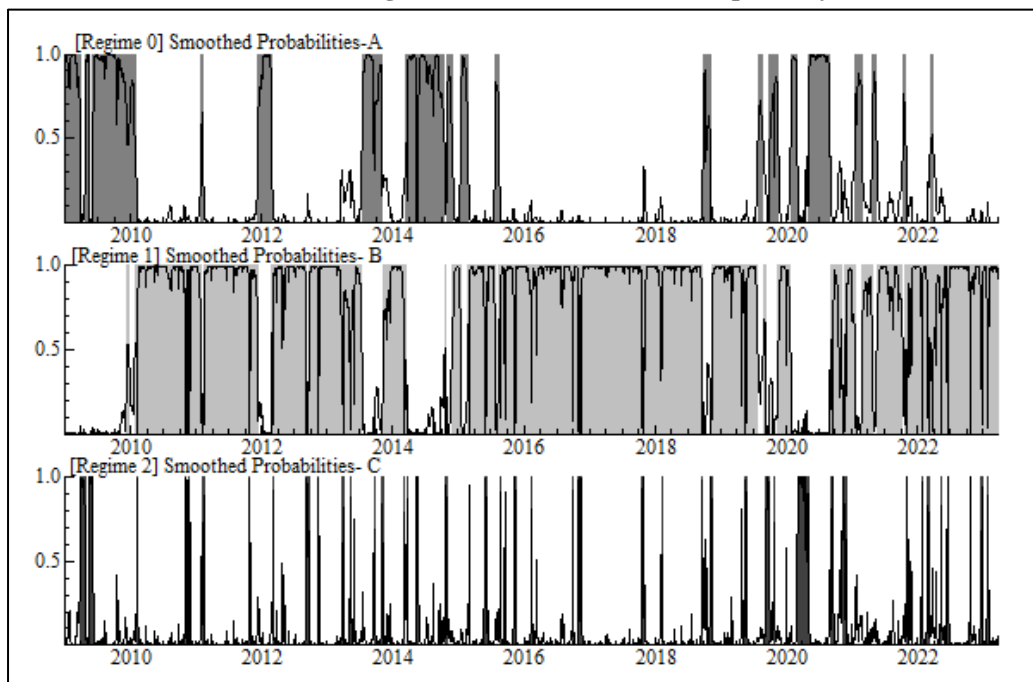
The possible reason for this is the Global Financial Crisis (GFC) or subprime crisis, which started approximately in 2007 and continued until 2009 (Bekiros et al., 2017; Litimi, 2017). The reason may be, like any other developed and emerging country, the Indian stock market crashed during the global economic turmoil, so the investor ignored their information and followed the overall market during uncertainty. However, as the high volatility regime persisted during that time, Indian investors stopped pursuing each other. This means the GFC crisis spillover effect is longer, i.e., 88 days, during the entire period.

Next, the market is in extreme volatility from March 2013 to June 2013, showing significant herding. It may be due to the ‘Taper-Tantrum’. The US Federal Reserve slowed the treasury bond purchases to revive the market from the financial crisis, increasing the bond yield. This leads to an outflow of FIIs from the Indian market and a market crash from the end of May to the end of August (Modak, 2021; Roychoudhury, 2021). This major sell-off may have led to sell-side herding by Indian investors. Next, extreme volatility was observed from 16-05-2014 to 21-05-2014. The Indian market is extremely volatile due to the Lok Sabha election result announced on 16th May 2014. Investors have become highly optimistic and started purchasing shares uniformly, hoping to earn excess returns (Kumar, 2019).

An extreme volatility regime can also be observed from 05-03-2020 to 05-05-2020. This extreme volatility was caused by the FII outflows due to coronavirus outbreak, and the fact that World Health Organisation (WHO) recognised COVID-19 as a pandemic on 11th March 2020. The uncertainty and volatility increased worldwide after the pandemic (Ali et al., 2020; Saini et al., 2023). The negative sentiments and high uncertainty led to a herd mentality in the Indian financial market during that period. Also, the Indian government announced Janata Curfew on 22nd March 2020 and lockdown policies to be followed from 24th March 2020 (Bora & Basistha, 2021). So, the adverse shocks further stimulated uncertainty and volatility, especially in BSE Sensex in the Indian financial market (Bora & Basistha, 2021).

Bharti and Kumar (2021) clearly state that volatility stimulated the herd mentality among Indian participants during the pandemic. However, in April 2020, the market moved very high again due to the relaxation in lockdown policy by the Indian government in April 2020 and the introduction of various stimulus packages for economic revival (Bharti & Kumar, 2021; Bora & Basistha, 2021). Ampofo et al. (2023) specify that the pandemic has also increased herding in developed countries. Figure 2 (A-C) highlights the smoothed probabilities of all three regimes. The smoothed probabilities graphs also depict the switching of different regimes. We found the order of low, high, and extreme volatility patterns for the Indian market. The market is usually in a highly volatile regime before extreme volatility. This shows that investors can predict the market will crash or become extremely volatile, so they should reframe their market portfolio strategy. We have also seen the Indian market go into high volatility after a sudden crash or extreme volatility, showing volatility clustering. This depicts the bidirectional switching of the extreme and high volatility regimes similar to the findings of Balcilar and Demirer (2015).

**Figure 2: Smoothed Regime Probabilities for Regime 0 (High Volatile), Regime 1 (Low Volatile), and Regime 2 (Extreme Volatile), Respectively**



## Conclusion

This research takes a deep dive into the dynamic nature of herd behaviour in the Indian financial market for 2009-2023 using the Markov Regime Switching and linear OLS regression models. We employ Chang et al. (2000)'s base model for measuring uniformity. The results of the static model show no herding across the whole sample period. The results of no herding corroborate the findings of Ansari and Ansari (2021) and Kanojia et al. (2022). The regime model identifies three regimes as high (Regime 0), low (regime 1), and extreme volatility regime (Regime 2), respectively. Our findings demonstrate significant herding in crash or extreme volatile regime. However, we find frequent switching of extremely volatile regimes with significant herding, which lasts only on average for approximately four days., The long-lasting, extremely volatile regimes with significant herding are 2009, 2013-2014, and 2020, due to unprecedented events like the GFC crisis, Taper-tantrum, presidential election, and COVID-19 pandemic. A recent study, Sachdeva et al. (2021), clearly states that information uncertainty increases the uniformity in the Indian market. Moreover, the study exhibits anti-herding during the high and low volatile regimes. The findings of anti-herding in a low volatile regime are in line with those of Fu and Wu (2021) because investors make decisions rationally at times of

certainty. We observe the pattern of low, high, and crash/extreme volatility in the Indian capital market. This suggests that investors can predict extreme or crash situations because the market first enters into low volatility followed by high and then crashes. The outcomes of our research are significant for investors and market regulators. Investors should form an appropriate strategy to readjust their market portfolio at 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 regulations continuously improve and information transmission becomes 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 more extensive portfolios at times of high volatility to maintain the same level of diversification (Chiang & Zheng, 2010; Fu & Wu, 2021). Bidirectional switching in extreme and highly volatile regimes guides market regulators in making a mechanism during crises or intense periods to stop the market from going into extreme situations (Balcilar & Demirer, 2015). This research adds new insights into Indian herding literature by adding evidence for dynamic herding in the Indian stock market. It will guide the researchers to add new dimensions to the same to further explore this aspect. The study is limited to only 338 companies out of 500. A separate study will also be conducted on the remaining companies, which may affect herding. Moreover, we only consider static transition probabilities in the study. Further research can be conducted by considering other exogenous variables like market sentiments or global factors that impact 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.

### **Declaration of Conflicting Interests**

The authors declared no potential conflict of interest with respect to the research, authorship, and publication of this article.

### **References**

- Akinsomi, O., Coskun, Y., Gupta, R., & Lau, C. K. M. (2018). Impact of volatility and equity market uncertainty on herd behaviour: Evidence from UK REITs. *Journal of European Real Estate Research*, 11(2), 169–186. <https://doi.org/10.1108/JERER-06-2017-0021>
- Ali, M., Alam, N., & Rizvi, S. A. R. (2020). Coronavirus (COVID-19): An epidemic or pandemic for financial markets. *Journal of Behavioral and Experimental Finance*, 27, 100341. <https://doi.org/10.1016/j.jbef.2020.100341>

- Ali, R., & Afzal, M. (2012). Impact of global financial crisis on stock markets: Evidence from Pakistan and India. *E3 Journal of Business Management and Economics*, 3(7), 275–282.  
[https://www.e3journals.org/cms/articles/1342846725\\_Afzal.pdf](https://www.e3journals.org/cms/articles/1342846725_Afzal.pdf)
- Ampofo, R. T., Aidoo, E. N., Ntiamoah, B. O., Frimpong, O., & Sasu, D. (2023). An empirical investigation of COVID-19 effects on herding behaviour in USA and UK stock markets using a quantile regression approach. *Journal of Economics and Finance*, 47(2), 517–540. <https://doi.org/10.1007/s12197-022-09613-8>
- Ansari, A., & Ansari, V. A. (2021). Do investors herd in emerging economies? Evidence from the Indian equity market. *Managerial Finance*, 47(7), 951–974.  
<https://doi.org/10.1108/MF-06-2020-0331>
- Arjoon, V., & Bhatnagar, C. S. (2017). Dynamic herding analysis in a frontier market. *Research in International Business and Finance*, 42, 496–508.  
<https://doi.org/10.1016/j.ribaf.2017.01.006>
- Avery, C., & Zemsky, P. (1998). Multidimensional uncertainty and herd behavior in financial markets. *American Economic Review*, 88(4), 724–748.  
<https://www.jstor.org/stable/117003>
- Babalos, V., Balcilar, M., & Gupta, R. (2015). Herding behavior in real estate markets: Novel evidence from a Markov switching model. *Journal of Behavioral and Experimental Finance*, 8, 40–43.  
<https://doi.org/10.1016/j.jbef.2015.10.004>
- Balcilar, M., & Demirer, R. (2015). Effect of global shocks and volatility on herd behavior in an emerging market: Evidence from Borsa Istanbul. *Emerging Markets Finance and Trade*, 51(1), 140–159.  
<https://doi.org/10.1080/1540496X.2015.1011520>
- Balcilar, M., Demirer, R., & Hammoudeh, S. (2013). Investor herds and regime-switching: Evidence from Gulf Arab stock markets. *Journal of International Financial Markets, Institutions and Money*, 23(1), 295–321.  
<https://doi.org/10.1016/j.intfin.2012.09.007>
- Bekiros, S., Jlassi, M., Lucey, B., Naoui, K., & Uddin, G. S. (2017). Herding behavior, market sentiment, and volatility: Will the bubble resume? *The North American Journal of Economics and Finance*, 42, 107–131.  
<https://doi.org/10.1016/j.najef.2017.07.005>
- Benkraiem, R., Bouattour, M., Galariotis, E., & Miloudi, A. (2021). Do investors in SMEs herd? Evidence from French and UK equity markets. *Small Business Economics*, 56(4), 1619–1637. <https://doi.org/10.1007/s11187-019-00284-0>
- Bharti., & Kumar, A. (2021). Exploring herding behaviour in Indian equity market during COVID-19 pandemic: Impact of volatility and government response. *Millennial Asia*, 13(3), 513–531. <https://doi.org/10.1177/09763996211020687>

- Bhatia, M. (2022). Stock market efficiency and COVID-19 with multiple structural breaks: Evidence from India. *Global Business Review*.  
<https://doi.org/10.1177/09721509221110372>
- Bikhchandani, S., Hirshleifer, D., & Welch, I. (1992). A theory of fads, fashion, custom, and cultural change as informational cascades. *Journal of Political Economy*, 100(5), 992–1026. <https://www.jstor.org/stable/2138632>
- Bikhchandani, S., & Sharma, S. (2000). Herd behavior in financial markets. *IMF Staff Papers*, 47(3), 279–310. <https://doi.org/10.2307/3867650>
- Blasco, N., Corredor, P., & Ferreruella, S. (2012). Does herding affect volatility? Implications for the Spanish stock market. *Quantitative Finance*, 12(2), 311–327. <https://doi.org/10.1080/14697688.2010.516766>
- Bora, D., & Basistha, D. (2021). The outbreak of COVID-19 pandemic and its impact on stock market volatility: Evidence from a worst-affected economy. *Journal of Public Affairs*, 21(4), e2623. <https://doi.org/10.1002/pa.2623>
- Brooks, C. (2008). *Introductory econometrics for finance* (2<sup>nd</sup> ed.). Cambridge University Press. <https://doi.org/DOI:10.1017/CBO9780511841644>
- Chang, E. C., Cheng, J. W., & Khorana, A. (2000). An examination of herd behavior in equity markets: An international perspective. *Journal of Banking and Finance*, 24(10), 1651–1679. [https://doi.org/10.1016/S0378-4266\(99\)00096-5](https://doi.org/10.1016/S0378-4266(99)00096-5)
- Chauhan, Y., Ahmad, N., Aggarwal, V., & Chandra, A. (2020). Herd behaviour and asset pricing in the Indian stock market. *IIMB Management Review*, 32(2), 143–152. <https://doi.org/10.1016/j.iimb.2019.10.008>
- Chiang, T. C., & Zheng, D. (2010). An empirical analysis of herd behavior in global stock markets. *Journal of Banking and Finance*, 34(8), 1911–1921. <https://doi.org/10.1016/j.jbankfin.2009.12.014>
- Choi, K. H., & Yoon, S. M. (2020). Investor sentiment and herding behavior in the Korean stock market. *International Journal of Financial Studies*, 8(2), 34. <https://doi.org/10.3390/ijfs8020034>
- Christie, W. G., & Huang, R. D. (1995). Following the pied piper: Do individual returns herd around the market? *Financial Analysts Journal*, 51(4), 31–37. <https://doi.org/10.2469/faj.v51.n4.1918>
- Cont, R. (2010). Empirical properties of asset returns: Stylized facts and statistical issues. *Quantitative Finance*, 1(2), 223–236. <https://doi.org/10.1080/713665670>
- Davies, R. B. (1987). Hypothesis testing when a nuisance parameter is present only under the alternatives. *Biometrika*, 74(1), 33–43. <https://doi.org/10.2307/2336019>
- Fei, T., & Liu, X. (2021). Herding and market volatility. *International Review of Financial Analysis*, 78, 101880. <https://doi.org/10.1016/j.irfa.2021.101880>

- Ferreruela, S., & Mallor, T. (2021). Herding in the bad times: The 2008 and COVID-19 crises. *The North American Journal of Economics and Finance*, 58, 101531. <https://doi.org/10.1016/j.najef.2021.101531>
- Fu, J., & Wu, L. (2021). Regime-switching herd behavior: Novel evidence from the Chinese A-share market. *Finance Research Letters*, 39, 101652. <https://doi.org/10.1016/j.frl.2020.101652>
- Galariotis, E. C., Rong, W., & Spyrou, S. I. (2015). Herding on fundamental information: A comparative study. *Journal of Banking and Finance*, 50, 589–598. <https://doi.org/10.1016/j.jbankfin.2014.03.014>
- Ganesh, R., Naresh, G., & Thiagarajan, S. (2017). The reflection of crowd behaviour in Indian bourses. *International Journal of Behavioural Accounting and Finance*, 6(2), 93. <https://doi.org/10.1504/IJBAF.2017.086408>
- Garg, A., & Gulati, R. (2013). Do investors herd in Indian market. *Decision*, 40(3), 181–196. <https://doi.org/10.1007/s40622-013-0015-z>
- Gebka, B., & Wohar, M. E. (2013). International herding: Does it differ across sectors? *Journal of International Financial Markets, Institutions and Money*, 23(1), 55–84. <https://doi.org/10.1016/j.intfin.2012.09.003>
- Gleason, K. C., Mathur, I., & Peterson, M. A. (2004). Analysis of intraday herding behavior among the sector ETFs. *Journal of Empirical Finance*, 11(5), 681–694. <https://doi.org/10.1016/j.jempfin.2003.06.003>
- Hamilton, J. D. (1989). A new approach to the economic analysis of nonstationary time series and the business cycle. *Econometrica*, 57(2), 357. <https://doi.org/10.2307/1912559>
- Hung, N. T. (2019). Return and volatility spillover across equity markets between China and Southeast Asian countries. *Journal of Economics, Finance and Administrative Science*, 24(47), 66–81. <https://doi.org/10.1108/JEFAS-10-2018-0106>
- Hwang, S., & Salmon, M. (2004). Market stress and herding. *Journal of Empirical Finance*, 11(4), 585–616. <https://doi.org/10.1016/j.jempfin.2004.04.003>
- Javaira, Z., Sahar, N. U., Hashmi, S. D., & Naz, I. (2023). Volatility and dynamic herding in energy sector of developed markets during COVID-19: A Markov regime-switching approach. *Fudan Journal of the Humanities and Social Sciences*, 17(1), 115–138. <https://doi.org/10.1007/s40647-023-00395-9>
- Jebbar, K., & Iqbal, A. (2016). Examining volatility spillover between Asian countries' stock markets. *China Finance and Economic Review*, 4(1), 1–13. <https://doi.org/10.1186/s40589-016-0031-1>
- Kabir, M. H., & Shakur, S. (2018). Regime-dependent herding behavior in Asian and Latin American stock markets. *Pacific-Basin Finance Journal*, 47, 60–78. <https://doi.org/10.1016/j.pacfin.2017.12.002>

- Kanojia, S., Singh, D., & Goswami, A. (2022). Impact of herding on the returns in the Indian stock market: An empirical study. *Review of Behavioral Finance*, 14(1), 115–129. <https://doi.org/10.1108/RBF-01-2020-0017>
- Klein, A. C. (2013). Time-variations in herding behavior: Evidence from a Markov switching SUR model. *Journal of International Financial Markets, Institutions and Money*, 26, 291–304. <https://doi.org/10.1016/j.intfin.2013.06.006>
- Kumar, A., Bharti, & Bansal, S. (2016). An examination of herding behavior in an emerging economy: A study of Indian stock market. *Global Journal of Management and Business Research*, 16(B55), 57–63. <https://journalofbusiness.org/index.php/GJMBR/article/view/101208>
- Kumar, C. (2019, May 22). *How the Sensex, Nifty reacted after Modi won 2014 elections*. Business Today. <https://www.businesstoday.in/markets/stocks/story/how-the-sensex-nifty-reacted-after-modi-won-2014-elections-201620-2019-05-22>
- Lakonishok, J., Shleifer, A., & Vishny, R. W. (1992). The impact of institutional trading on stock prices. *Journal of Financial Economics*, 32(1), 23–43. [https://doi.org/10.1016/0304-405X\(92\)90023-Q](https://doi.org/10.1016/0304-405X(92)90023-Q)
- Lao, P., & Singh, H. (2011). Herding behaviour in the Chinese and Indian stock markets. *Journal of Asian Economics*, 22(6), 495–506. <https://doi.org/10.1016/j.asieco.2011.08.001>
- Litimi, H. (2017). Herd behavior in the French stock market. *Review of Accounting and Finance*, 16(4), 497–515. <https://doi.org/10.1108/RAF-11-2016-0188>
- Mand, A. A., & Sifat, I. (2021). Static and regime-dependent herding behavior: An emerging market case study. *Journal of Behavioral and Experimental Finance*, 29, 100466. <https://doi.org/10.1016/j.jbef.2021.100466>
- Mertler, C. A., Vannatta, R. A., & LaVenja, K. N. (2021). *Advanced and multivariate statistical methods : Practical application and interpretation* (7<sup>th</sup> ed.). Routledge. <https://doi.org/10.4324/9781003047223>
- Modak, S. (2021, February 27). *Market sell-off brings back memories of the 2013 “taper tantrum”*. Business Standard. [https://www.business-standard.com/article/markets/market-sell-off-brings-back-memories-of-the-2013-taper-tantrum-121022700045\\_1.html](https://www.business-standard.com/article/markets/market-sell-off-brings-back-memories-of-the-2013-taper-tantrum-121022700045_1.html)
- Mukherjee, P., & Tiwari, S. (2022). Trading behaviour of foreign institutional investors: Evidence from Indian stock markets. *Asia-Pacific Financial Markets*, 29(4), 605–629. <https://doi.org/10.1007/s10690-022-09361-z>
- Newey, W. K., & West, K. D. (1987). A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. *Econometrica*, 55(3), 703–708. <https://doi.org/10.2307/1913610>



- Nguyen, Y. V. B., & Vo, A. H. K. (2023). Herding behavior before and after COVID-19 pandemic: Evidence from the Vietnam stock market. *Journal of Economic Studies*, 5(2), 357-374. <https://doi.org/10.1108/JES-01-2023-0031>
- Poshakwale, S., & Mandal, A. (2014). Investor behaviour and herding: Evidence from the national stock exchange in India. *Journal of Emerging Market Finance*, 13(2), 197–216. <https://doi.org/10.1177/0972652714541341>
- Rompotis, G. G. (2018). Herding behavior among exchange-traded funds. *Journal of Behavioral Finance*, 19(4), 483–497. <https://doi.org/10.1080/15427560.2018.1431886>
- Roychoudhury, A. (2021, March 26). *Explained: The 2013 taper tantrum and why its spectre is being raised again*. Money Control. <https://www.moneycontrol.com/news/business/economy/explained-the-2013-taper-tantrum-and-why-its-spectre-is-being-raised-again-6700731.html>
- Sachdeva, M., Lehal, R., Gupta, S., & Garg, A. (2021). What make investors herd while investing in the Indian stock market? A hybrid approach. *Review of Behavioral Finance*, 15(1), 19-37. <https://doi.org/10.1108/RBF-04-2021-0070>
- Saini, C., Sharma, I., Verma, B., & . B. (2023). Performance of equity ETFs during COVID-19 pandemic crisis: Evidence from India. *Abhigyan*, 41(3), 21–31. <https://www.ischolar.in/index.php/Abhigyan/article/view/223672>
- Scharfstein, D. S., & Stein, J. C. (1990). Herd behavior and investment. *The American Economic Review*, 80(3), 465–479. <https://www.jstor.org/stable/2006678>
- Schmitt, N., & Westerhoff, F. (2017). Herding behaviour and volatility clustering in financial markets. *Quantitative Finance*, 17(8), 1187–1203. <https://doi.org/10.1080/14697688.2016.1267391>
- Sen, R., & Subramaniam, M. (2019). Stylized facts of the Indian stock market. *Asia-Pacific Financial Markets*, 26(4), 479–493. <https://doi.org/10.1007/s10690-019-09275-3>
- Shakya, A., Michael, S., Saunders, C., Armstrong, D., Pandey, P., Chalise, S., & Tonkoski, R. (2017). Solar irradiance forecasting in remote microgrids using Markov switching model. *IEEE Transactions on Sustainable Energy*, 8(3), 895–905. <https://ieeexplore.ieee.org/abstract/document/7745906>
- Shiller, R. J., Fischer, S., & Friedman, B. M. (1984). Stock prices and social dynamics. *Brookings Papers on Economic Activity*, 1984(2), 457. <https://doi.org/10.2307/2534436>
- Shrotryia, V. K., & Kalra, H. (2022). Herding and BRICS markets: A study of distribution tails. *Review of Behavioral Finance*, 14(1), 91–114. <https://doi.org/10.1108/RBF-04-2020-0086>

- Singh, A., & Singh, M. (2017). Risk–return relationship in BRIC equity markets: Evidence from Markov regime switching model with time-varying transition probabilities: *Metamorphosis: A Journal of Management Research*, 15(2), 69–78. <https://doi.org/10.1177/0972622516675814>
- Spyrou, S. (2013). Herding in financial markets: A review of the literature. *Review of Behavioral Finance*, 5(2), 175–194. <https://doi.org/10.1108/RBF-02-2013-0009>
- Tan, L., Chiang, T. C., Mason, J. R., & Nelling, E. (2008). Herding behavior in Chinese stock markets: An examination of A and B shares. *Pacific Basin Finance Journal*, 16(1–2), 61–77. <https://doi.org/10.1016/j.pacfin.2007.04.004>
- Tauseef, S. (2023). Herd behaviour in an emerging market: An evidence of calendar and size effects. *Journal of Asia Business Studies*, 17(3), 639–655. <https://doi.org/10.1108/JABS-10-2021-0430>
- Trueman, B. (1994). Analyst forecasts and herding behavior. *Review of Financial Studies*, 7(1), 97–124. <https://doi.org/10.1093/rfs/7.1.97>
- Wermers, R. (1999). Mutual fund herding and the impact on stock prices. *Journal of Finance*, 54(2), 581–622. <https://doi.org/10.1111/0022-1082.00118>
- Yang, W. R., & Chuang, M. C. (2023). Do investors herd in a volatile market? Evidence of dynamic herding in Taiwan, China, and US stock markets. *Finance Research Letters*, 52, 103364. <https://doi.org/10.1016/j.frl.2022.103364>
- Yao, J., Ma, C., & He, W. P. (2014). Investor herding behaviour of Chinese stock market. *International Review of Economics and Finance*, 29, 12–29. <https://doi.org/10.1016/j.iref.2013.03.002>