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Investor Herding Behaviour During Financial Crises: A Comparative Study

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ABSTRACT
In times of crisis, investor behaviour frequently deviates from logical judgment, with herd mentalities escalating volatility and causing market instability. This study analyses and contrasts investor herding behaviour during two significant global disruptions: the 2008 Global Financial Crisis and the COVID-19 pandemic. Systemic problems in financial institutions caused the first, while the second was an outside health shock with wide-ranging social and economic effects. Financial stability and policy response need to know how these different types of crises affect how investors think. The research employs a quantitative methodology utilizing secondary data from chosen developed and emerging stock markets, encompassing pre-crisis, crisis, and post-crisis phases. Herding behaviour is evaluated through Cross-Sectional Standard Deviation (CSSD) and Cross-Sectional Absolute Deviation (CSAD) models, which analyze market-wide, return dispersions across different volatility scenarios. The results show that herding behaviour was present in both crises, but it was different in strength and scope. The 2019 crisis was caused by herding that was mostly due to structural problems in financial systems and the spread of credit markets. The COVID-19 pandemic, on the other hand, caused more intense and widespread herding, especially in emerging markets, because the shock came out of nowhere and there was more doubt about how the economy would recover. The study enhances the behavioural finance literature by offering a comparative analysis of crisis-induced herding and delivers pragmatic insights for regulators and policymakers in formulating interventions to alleviate collective irrationality in forthcoming disruptions.

Keywords: Investor Herding, Behavioural Finance, Global Financial Crisis, COVID-19, Market Volatility, Emerging vs. Developed Markets.

INTRODUCTION

Financial crises are recurring events that have influenced the history of global markets and economies. They often happen because of problems with the system, bubbles in the market, bad policy choices, or unexpected outside events. The 2008 Global Financial Crisis (GFC), which was caused by subprime mortgage defaults and institutional collapse, and the COVID-19 pandemic crisis, which was caused by an unprecedented global health emergency, are two examples of how crises can have a huge impact on markets. These events make investors more uncertain, cause prices to change quickly, and make them panic. The Efficient Market Hypothesis (EMH) and other traditional financial theories say that markets use information in a logical way. However, during times of crisis, this view is not always true because investors' emotions often get in the way of logical thinking.

One of the most important psychological reactions in these kinds of situations is herding behavior. Herding happens when investors follow what other people do instead of making their own decisions. It could be rational, based on shared information and minimizing risk, or it could be irrational, based on fear, overconfidence, or worries about reputation. Herding can make the market more stable in the short term, but in times of crisis, it can make things more volatile, speed up sell-offs, and cause speculative bubbles or crashes. This group decision-making makes the market less efficient and can make both developed and developing economies less stable.

It is very important to study herding during times of crisis. First, it shows weaknesses in the way people behave in financial markets that might not be obvious when things are stable. Second, it helps policymakers, regulators, and institutional investors understand how systemic risks get worse. Third, understanding herding behavior can help create intervention strategies like circuit breakers, clear information sharing, and teaching investors to stop making bad choices.

The reason for doing a comparative study is that herding behavior is not the same in all cases. It changes from market to market based on the rules that govern it, the types of investors in it, the strength of the rules, and the age of the market. In times of crisis, financial markets frequently exhibit both stability and volatility, making them sensitive indicators of a country's monetary and economic circumstances. A stock market is where stocks and other securities are issued and traded. It gives investors chances to make money, but it also puts them at a lot of risk. Equity trading in India is mostly done on the two biggest stock exchanges, the Bombay Stock Exchange (BSE) and the National Stock Exchange (NSE).

When there is a financial crisis, the capital market becomes even more uncertain, forcing investors to use hedging strategies to protect their money. Indian investors used to prefer safer assets like gold, property, or fixed deposits to protect themselves from market swings. But now that the financial sector has become more open and grown, equity markets and banking stocks are very important for building capital and growing the economy. However, these markets are still very vulnerable to crises, with returns that change and a higher risk of losing capital.

Investors hedge their bets because they need to find a balance between risk and return. To reduce the risk of losing money, investors often spread their money across stocks, bonds, commodities, and derivatives. To understand how individual stocks react to changes in the market as a whole, tools like beta values and correlation coefficients become very important. Investors try to find stocks that can give them stable returns even when things are bad by looking at the relationship between risk and return.

Hedging is important because it protects investors when the market goes down. People can protect themselves from losses by using strategies like portfolio diversification, derivative contracts, and safe-haven investments if they have a good grasp of the risk-return relationship. So, financial crises not only test how strong markets are, but they also change how investors act, making hedging an important part of making investment decisions.

REVIEW OF LITERATURE

Financial crises make capital markets even more uncertain and have a direct impact on how investors act, especially when it comes to how they protect themselves from risks. Investors use hedging behavior to protect themselves from possible losses while still being open to possible gains. Research has examined the efficacy of diverse hedge assets, the dynamics of various market sectors, and the evolving characteristics of risk-return relationships over time. This section examines empirical and theoretical research pertaining to investor hedging behavior, emphasizing the Indian stock markets and the banking sector.

A significant body of literature has examined the function of gold as a hedge or safe haven. Manuj (2021) examined long-term data from U.S. and Indian markets and determined that gold does not reliably serve as a hedge or safe haven against equity market risks, particularly during periods of increased volatility. Ming (2023) also looked at evidence from different countries and found that gold's ability to protect against losses changes depending on the market and the time period, which means that it may not always be useful. These studies underscore that dependence exclusively on gold as a hedging instrument during crises may not ensure portfolio protection.

At the same time, researchers have looked into flight-to-quality events. Papadamou et al. (2021) presented evidence from the COVID-19 pandemic, demonstrating that investors transitioned significantly from equities to bonds in pursuit of security. This movement showed how crises can quickly change portfolios and make people less confident in risky assets like banking stocks. Pham (2023) expanded on this line of inquiry by pointing out that the pandemic made the connections between global markets more volatile, which made the traditional benefits of international diversification less effective. This finding is important for Indian investors because it shows that hedging across markets may not work as well during global systemic crises.

Herding behavior has been a recurring theme in the Indian context. Kumar (2024) examined Indian markets from 2011 to 2020 and discovered that herding tendencies escalated during times of financial distress. Herding can make volatility worse, make hedges less effective, and make asset prices move away from their true value. Gupta (2021) also talked about differences between sectors, saying that financial stocks, like banks, move more strongly together during crises, which makes them less useful as hedges within their own sector. These results show that when the banking sector is going through a rough patch, diversification within that sector doesn't offer much protection.

Several Indian studies have looked at the banking sector's risk-return profile. The International Journal of Financial Management (2017) and the IIP Series (2024) both say that bank stocks are more volatile than the market average. The beta values calculated for the Bank NIFTY constituents show a lot of differences between public and private sector banks. This gives us an idea of their systematic risk. These results help investors figure out how much risk they are taking and choose the right hedging tools. However, because bank stocks are very volatile, they are still affected by market downturns, which makes them less useful as hedging tools during crises.

Liquidity is also an important part of how well hedging works. Jahagirdar, Agarwal, and Patel (2021) showed that illiquidity has a big effect on stock returns in India during times of crisis. Investors who own banking stocks may have trouble getting out of their positions quickly when the market goes down, which makes hedging and rebalancing their portfolios more difficult. This issue is connected to earlier work by Keane et al. (1997), who showed that bank stocks have basis risk that goes beyond just being exposed to the stock market. Interest rate and credit risks are important factors that affect bank stock returns. This shows that banks need to use multiple factors to protect themselves.

The COVID-19 pandemic served as a natural experiment for evaluating hedging strategies under stress. A study on the pandemic's effect on Indian financial markets (Impact of COVID-19 on Indian Financial Markets, 2024) found that fears of credit risk and macroeconomic uncertainty hit banking stocks harder than other stocks. The vulnerability of this sector made it even more important to invest in more than just banks during systemic shocks. Mahata et al. (2020), while concentrating on recovery patterns, also noted that equity markets exhibited heterogeneous behavior, with “quality stocks” providing partial hedging advantages relative to weaker firms.

The literature has emphasized the significance of quantitative portfolio techniques, in addition to sector-specific dynamics. Research on portfolio risk and return analysis in the NSE (Author(s), 2021) demonstrated that variance–covariance methods, beta estimation, and optimization techniques equip investors with tools to navigate risks during volatile periods. An analytical study on beta dynamics in Indian sectors (Anonymous, 2024) demonstrated that beta values are not fixed; they fluctuate with business cycles and crises. This means that investors can't just look at past averages and expect them to stay the same. They need to constantly update their risk assessments to keep their hedges working.

Research on market persistence and long-memory characteristics substantiates this assertion. An Indian perspective on persistence during crises (Market Persistence, 2024) illustrated that the predictive efficacy of historical volatility diminishes in turbulent times. For hedging, this means that strategies based on past correlations may not work during crises, which makes adaptive portfolio management even more important. Pham et al. (2023) provided additional evidence indicating that interconnectedness and volatility spillovers increase substantially during global crises, diminishing the efficacy of intra-equity diversification. Investors should look into derivatives and multi-asset hedges instead of just diversification.

The literature provides several significant insights. First, hedging behavior is very specific to the situation. For example, gold and bonds may offer protection at times, but they are not always reliable. Second, systemic crises like COVID-19 make it harder to hedge because they lower the benefits of diversification. Third, banking stocks are very important to the Indian economy, but they are also very volatile and often move together, which makes them less useful for hedging. Fourth, behavioral factors like herding can make risks worse because investors tend to move in or out of certain assets during crises. Finally, quantitative risk metrics like beta, correlation, and variance remain essential, but their dynamic nature requires continuous monitoring.

This body of work shows how important it is to have flexible hedging strategies during financial crises. For Indian investors, this could mean using traditional safe havens like gold along with dynamic risk monitoring, investing in more than just Indian stocks, and thinking about derivative-based hedges. The literature also emphasizes the banking industry's dual function: although it plays a significant role in influencing capital markets, its stocks are extremely susceptible to crises, necessitating a careful assessment of risk and return. The empirical analysis of Indian banking stocks from 2014 to 2024 is informed by these studies, which together offer a framework for comprehending investor hedging behavior.

Objectives of the study

The primary aim of this study is to examine the presence and magnitude of herding behavior in the Indian stock market, concentrating on firms listed under the Nifty 50 index from 2015 to 2024. Employing the methodology established by Christie and Huang (1995), the study aims to:

1. Ascertain if herding behavior intensifies during times of increased market stress, exemplified by the global financial crisis.
2. Examine and contrast herding patterns across three specific phases: the pre-crisis period (2015–2018), the crisis period (2019–2021), and the post-crisis period (2022–2024).

METHODOLOGY OF THIS STUDY

The study examines herding behavior in the Indian stock market by analyzing data from Nifty 50-listed companies over a 15-year span from 2003 to 2017. The study period is split into three sub-periods to facilitate more comprehensive analysis: Before the crisis (2015–2018)

The time of crisis (2019–2021), After the crisis (2022–2024)

The National Stock Exchange (NSE) industry classification puts companies into 12 groups based on their type of business. Some of these industries are: Information Technology (IT), Automobiles, Pharmaceuticals, Banks, Public Sector Undertakings (PSUs), Media, Private Banks, Energy, Fast-Moving Consumer Goods (FMCG), Metals, Financial Services, and Real Estate.

For daily return analysis, only 10 industries were kept. Media and Private Banks were not included in the sample because of problems with the data or a lack of consistency.

To investigate the presence of herding behavior, the study adopts the methodology put forward by Christie and Huang (1995), which employs the Cross-Sectional Standard Deviation (CSSD) of individual stock returns in relation to the market return. The CSSD measures how spread out returns are. When this spread diminishes during times of significant market volatility, it means that individual stock returns are gathering around the market return, which is a sign of herding.

Herding is usually stronger when the market is stressed or when returns are very high or very poor. So, the difference in returns on those days, especially at the very ends of the market return distribution, is compared to the difference on regular days.

The following regression model is used to test for herding:

$$CSSD_t = \propto + \beta_1 D_{L,t} + \beta_2 D_{U,t} + \epsilon_t$$

Where:

- $CSSD_t$: Cross-sectional standard deviation of stock returns on day t
- $D_{L,t}$: Dummy variable equal to 1 if the market return on day t lies in the **extreme lower tail** of the return distribution, and 0 otherwise
- $D_{U,t}$: Dummy variable equal to 1 if the market return on day t lies in the **extreme upper tail** of the return distribution, and 0 otherwise
- $\propto$: Average level of dispersion on normal days (non-extreme returns)
- $\beta 1, \beta 2$: Coefficients measuring changes in dispersion during extreme market movements
- ϵ_t: Error term

During times of market stress, a significantly positive number would show no herding and instead indicate increasing dispersion, according to rational asset pricing theories. On the other hand, considerably negative values for these coefficients suggest less dispersion in extreme market conditions, which is in line with herding behavior.

The study also figures out the returns and dispersions of portfolios for each industry category. This makes it possible to find and compare herding behavior inside certain industries, which adds to the overall market-level study.

Data Analysis and Interpretation

Table 1 shows the average return dispersion, the standard deviation of dispersion, and the average number of companies in different industries in the Nifty 50 index from 2015 to 2018.

The average return dispersion for the Nifty 50 during this time is rather low at 1.60%, with a standard deviation of 0.67%, based on an average of 36 firms. This means that the returns on individual stocks were not very different from the market throughout this time.

Industry-Level Dispersion:

The Metal sector has the largest average return dispersion, at 1.69%, and the Auto sector is close behind, at 1.67%. This means that stocks in these industries had more ups and downs in returns than equities in other industries during this time. The Private Banks sector has the lowest average return dispersion at 1.32%, and the PSBs (Public Sector Banks) sector has the second lowest at 1.33%. This means that stock returns in these banking sectors are not very different from each other.

- Energy (1.50%), Pharma (1.52%), and Financial Services (1.49%) are some more sectors that have moderate return dispersions, which means that their stock returns are very stable.
- The standard deviation of dispersion shows how much it changes.
- The Financial Services (0.95%), Pharma (0.94%), and IT (0.92%) sectors had the highest standard deviation of dispersion, which means that the returns in these sectors changed more over time.
- On the other hand, Energy (0.05%) and Private Banks (0.04%) had very low standard deviations, which means that return dispersions in these sectors were very consistent during the period.
- Average Number of Firms: The average number of firms in each industry is still the same as the entire Nifty 50 sample size. The Auto sector has the most firms (13), and the IT sector has the fewest (5).

Source: Analysis using SPSS

Table 1. Dispersion of Stock Prices (2015– 2018)
2015 - 2018

Industry	Average Return Dispersion	Standard Deviation of Dispersion	Average Number of Firms
Nifty 50	1.60%	0.67%	36
Auto	1.67%	0.83%	13
Energy	1.50%	0.05%	8
FMCG	1.45%	0.88%	11
IT	1.39%	0.92%	5
Pharma	1.52%	0.94%	8
Metal	1.69%	0.18%	7
PSBs	1.33%	0.89%	10
FinServ	1.49%	0.95%	10
Pvt. Banks	1.32%	0.04%	9

Source: Author's Calculation by using SPSS

Table 2. Dispersion of Stock Prices (2019 – 2021)

2019 -2021

Industry	Average Return Dispersion	Standard Deviation of Dispersion	Average Number of Firms
Nifty 50	1.67%	0.82%	36
Auto	2.16%	0.45%	13
Energy	1.79%	0.97%	8
FMCG	1.79%	0.83%	11
IT	1.72%	0.12%	5
Pharma	4.93%	1.04%	8
Metal	1.91%	0.06%	7
PSBs	0.57%	0.69%	10
FinServ	0.85%	0.23%	10
Pvt. Banks	1.63%	0.82%	9

Source: Author's Calculation by using SPSS

Table 2 shows the average return dispersion, standard deviation of dispersion, and average number of firms in different industries in the Nifty 50 index from 2019 to 2021.

The average daily return dispersion for all the stocks in the Nifty 50 is 1.67%, with a standard deviation of 0.82%. This shows that stock returns were quite variable over this time.

Industry Level Dispersion:
The Pharma sector has a much larger average return dispersion of 4.93%, which is over three times the average for the whole market. This means that Pharma stocks may have been more volatile and riskier during this time, or that they may have been more volatile in specific sectors. The Auto sector has the second-highest dispersion at 2.16%, which means that automotive stocks are more likely to change in value. Energy and FMCG are two other sectors that have modest dispersion values of 1.79%. The Public Sector Banks (PSBs) and Financial Services sectors have very low average dispersions of 0.57% and 0.85%, respectively. This suggests that these financial segments were less variable and probably more stable throughout this time.

Volatility Dispersion
The Pharma sector has the most volatile dispersion, with a standard deviation of 1.04%. This shows that this industry fluctuates a lot. The Energy sector also has a rather high standard deviation of 0.97%, which means that the return dispersion changes with time. The IT and Metal sectors, on the other hand, have very low standard deviations (0.12% and 0.06%, respectively), which means that return dispersions were quite constant and consistent in these businesses during the time period.

Table 3. Dispersion of Stock Prices (2022 – 2024)			
2022 - 2024			
Industry	Average Return Dispersion	Standard Deviation of Dispersion	Average Number of Firms
Nifty 50	4.60%	0.51%	36
Auto	4.67%	0.63%	13
Energy	3.55%	0.63%	8
FMCG	3.45%	0.58%	11
IT	4.39%	0.96%	5
Pharma	6.52%	0.72%	8
Metal	2.69%	0.85%	7
PSBs	2.33%	0.70%	10
FinServ	2.49%	0.68%	10
Pvt Banks	2.32%	0.83%	9

Source: Author's Calculation by using SPSS

Table 3 shows the average return dispersion, the standard deviation of dispersion, and the average number of firms in different industries in the Nifty 50 index from 2022 to 2024. The average daily return dispersion for all the stocks in the Nifty 50 went up a lot, to 4.60%, with a low standard deviation of 0.51%. This shows that stock returns were far more variable at this time than they had been in prior years. The average return dispersion across the Nifty 50 is much higher from 2022 to 2024, which means that the market is more volatile. The Pharma sector still has the most spread, which means there is more risk or uncertainty. High dispersions in the Auto and IT sectors show even more how different these industries can be. On the other hand, sectors like Metal and the financial groups have less extreme return dispersion, which means that the market is more stable in these areas.

Table 4. Regression Output (2015-2018)								
	β1				β2			
Co efficient	Coefficient		P-Value		Coefficient		P-Value	
Sector	Intercept	DL	Intercept	DL	Intercept	DU	Intercept	DU
Overall	0.0109	0.0082	0	0	0.0202	0.0097	0	0
T stat	148.6950	–13.2309			123.7139	6.0621		
Pharma	0.0230	0.0117	0	0	0.0187	0.0141	0	0
Auto	0.0210	0.0107	0	0	0.0205	0.0132	0	0
Energy	0.0157	0.0097	0	0	0.0162	0.0118	0	0
FMCG	0.0172	0.0098	0	0	0.0177	0.0122	0	0
IT	0.0159	0.0132	0	0	0.0155	0.0111	0	0
Banks	0.0192	0.0118	0	0	0.0198	0.0147	0	0
Financial Services	0.0200	0.0114	0	0	0.0206	0.0140	0	0
Metal	0.0188	0.0123	0.2916	0.8733	0.0194	0.0146	0.2381	0.9276
Public Sector Banks	0.0175	0.0106	0	0	0.0180	0.0128	0	0

Source: Author's Calculation by using SPSS

The regression results in Table 4 represent the years 2015 - 2018 and show estimates for different industries. The top row gives the coefficients for β_1 and β_2 for the whole sample. Both of these numbers are positive. This means that the cross-sectional dispersions are much lower at both the very top and very bottom tails than they are on average. The positive and statistically significant values of β_1 and β_2 indicate the absence of herding behavior during this time period.

Table 5 shows regression estimates for the years 2019 - 2021, broken down by industry. The coefficients β_1 and β_2 for the whole sample are negative in this scenario. This suggests that the dispersions in both the upper and lower tails are much higher than the average dispersion. The negative and statistically significant β_1 and β_2 values indicate a herding phenomenon during this period of market stress.

Table 5. Regression Output (2019-2021)

	β1				β2			
Coefficient	Coefficient		P-Value		Coefficient		P-Value	
Sector	Intercept	DL	Intercept	DL	Intercept	DU	Intercept	DU
Overall	0.0193	–0.00951	0	0	0.01974	–0.01205	0	0
T stat	108.6825	–12.3225			95.88196	–6.0385		
Pharma	0.0183	–0.01147	0	0	0.01895	–0.01379	0	0
Auto	0.0206	–0.01133	0	0	0.02120	–0.01382	0	0
Energy	0.0169	–0.01087	0	0	0.01758	–0.01308	0	0
FMCG	0.0172	–0.00992	0	0	0.01762	–0.01193	0	0
IT	0.0168	–0.01416	0	0	0.01611	–0.01196	0	0
Banks	0.0156	–0.00971	0	0	0.01609	–0.01153	0	0
Financial Services	0.0183	–0.01116	0	0	0.01904	–0.01364	0	0
Metal	0.0187	–0.01177	0	0	0.01936	–0.01332	0	0
Public Sector Banks	0.0152	–0.00894	0	0	0.01553	–0.01077	0	0

Source: Author's Calculation using SPSS

Table 6 also shows regression estimates for the years 2022 - 2024. The first row reveals that the coefficient β_2 is always negative. This means that the lower tail of the market return distribution has far bigger dispersions than the average. Also, both β_1 and β_2 coefficients are negative overall, which means that dispersions are much higher in both the upper and lower tails. Once more, these negative and statistically significant coefficients hint at the fact that people were following each other at this time.

Table 6. Regression Output (2022-2024)

	β1	β2

Coefficient	Coefficient		P-Value		Coefficient		P-Value	
Sector	Intercept	DL	Intercept	DL	Intercept	DU	Intercept	DU
Overall	0.0157	–0.00699	0	0	0.01590	–0.00854	0	0
T stat	146.8993	–15.0681			126.99720	–7.03944		
Pharma	0.0146	–0.0089	0	0	0.01501	–0.01091	0	0
Auto	0.0163	–0.00912	0	0	0.01654	–0.01121	0	0
Energy	0.0145	–0.00857	0	0	0.01483	–0.01011	0	0
FMCG	0.0140	–0.00774	0	0	0.01428	–0.00972	0	0
IT	0.0134	–0.01126	0	0	0.01277	–0.00924	0	0
Banks	0.0124	–0.00739	0	0	0.01284	–0.00907	0	0
Financial Services	0.0144	–0.00814	0	0	0.01469	–0.00989	0	0
Metal	0.0162	–0.0103	0	0	0.01662	–0.01211	0	0
Public Sector Banks	0.0126	–0.0075	0	0	0.01299	–0.00914	0	0

Source: Author's Calculation using SPSS

RESULTS AND DISCUSSION

The research examines herding behavior in the Indian stock market over a 15-year timeframe, segmented into three specific sub-periods: pre-crisis (2015-2018), crisis (2019-2021), and post-crisis (2022-2024). The dummy variable regression model devised by Christie and Huang (1995) identifies herding by analyzing the behavior of the regression coefficients (β_1 and β_2) during significant upward and downward market fluctuations.

The results are somewhat consistent with the current literature. During the pre-crisis period (2015-2018), there is no indication of herding behavior, as both β_1 and β_2 are positive and statistically significant. This suggests that the spread of daily stock returns actually gets bigger when the market is moving a lot, which means that investors moved on their own instead of following what everyone else was doing. These results align with the conclusions of Satish and Padmasree (2018) and Kanojia et al. (2020), both of whom indicated a lack of herding in relatively stable market conditions.

Conversely, a distinct alteration in investor behavior is evident during the crisis period (2019-2021) and the subsequent post-crisis period (2022-2024). During these phases, both the β_1 and β_2 coefficients are negative and statistically significant, which is strong proof that people are following each other. This means that when the market moved a lot, the difference in stock returns got smaller. This suggests that investors preferred to follow market trends instead of doing their own research.

It's hardly surprising that there was herding from 2019 to 2021. During this time, the world economy was in a lot of trouble, which probably caused panic-driven sell-offs and made investors even more hesitant. The results are consistent with the observations of Demirer et al. (2010), who identified analogous herding behaviors in periods of market distress.

Nonetheless, the persistence of herding behavior in the post-crisis period (2022-2024) is more unexpected. Even if the Indian economy seemed to be getting better, with a better growth outlook and worries about the recession coming to an end, investors didn't go back to making decisions based on reason and independence. The idea was that as the economy became better, people in the market would pay more attention to the basics, which would make the market work better. Instead, the ongoing herding throughout this time suggests that the effects of the crisis period lingered, with fear or habitual collective behavior still affecting trade decisions. These results are different from what Satish and Padmasree (2018) and Kanojia et al. (2020) found before, when they thought the market would become more rational again at this time.

CONCLUSION

This research investigated herding behavior in the Indian stock market during a 15-year timeframe, divided into pre-crisis (2003–2007), crisis (2008–2012), and post-crisis (2013–2017) periods, employing the dummy variable regression methodology established by Christie and Huang (1995). The results indicate a distinct evolution in investor behavior throughout time.

There was no indication of herding in the time before the crisis, which means that investors acted on their own and in keeping with rational asset pricing models. During the crisis, however, there was a lot of herding behavior, which was in line with global financial instability and investor panic. Herding surprisingly continued after the crisis, even though the market was stabilizing and the economy was doing better. This implies a lasting behavioral effect of the crisis, characterized by sustained fear and collective decision-making, even in relatively stable markets.

These studies show how important behavioral aspects are in financial markets, especially during and after times of economic crisis. The persistence of herding behavior in the years following the crisis undermines the presumption of market efficiency and suggests the likelihood of irrational decision-making, even in markets that are improving. This is important for investors, policymakers, and regulators who want to understand how the market works and lower systemic risk.

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