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The Impact of Crisis on Herding among Indian investors: An Empirical study

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Abstract

Herding occurs when the investors mimic the actions of others disregarding their own information or analysis. This anomaly becomes particularly noticeable during periods of crises, where anxiety and uncertainty dominate decision-making behaviour of investors. The present paper examines herding behaviour among investors in the Indian stock market during the overall period (2015-2024) as well as during various periods of crisis. It further explores the contagion effect between herding in USA and that in India. Using quantile regression model and cross-sectional absolute deviation (CSAD) technique, the paper studies daily data points of NIFTY 50 companies for a period of 10 years (1st April,2015 to 31st March,2024) to assess herding parameters. Dummy regression has been applied to compute herding during various crises namely: COVID-19, Russia-Ukraine war and Federal bank failure. The results suggest absence of herding during the overall period (2015-2024) which indicates that the market participants rely on their own knowledge and wisdom for financial decision making. However, this trend gets reversed during periods of turbulence, especially geo-political crisis where investors get together and behave collectively. Also, a strong contagion effect is observed between the market behaviour of US and Indian stock market.

Keywords: *Herding behavior, crisis, CSAD, stock market, dummy regression*

1. Introduction

Herding in financial markets refers to the behavioural manifestation of the market participants to imitate the investment decisions of fellow members who are perceived as more experienced and well-informed (Vo and Phan, 2019). Herding behaviour, mainly driven by cognitive shortcuts and mental urges, stands in contrast to the fundamental decision-making where investment choices are made on the basis of rationality and wisdom. During herding, market participants are largely swayed by psychological and behavioural influences which are a mix of mood, fear, anxiety, apprehension, optimism, pessimism, etc. that push investors to trade collectively (Bikchandani and Sharma, 2000). This flocking behaviour of investors, stemming from bounded rationality can, at times, negatively influence stock prices and market efficiency. Past literature on the subject validates that the propensity to herd has led to market inefficiencies several times, such as asset bubbles or market crashes like the dot-com bubble and the 2008 financial crisis (Banerjee, 1992; Shiller, 2000; Shrotriya and Kalra, 2019). The dynamics of cognitive impulses and herding, has been well captured by the domain of behavioural finance, describing how this peculiar interaction often leads to irrational investment choices. Hence, it becomes extremely important to analyse the herding effect as it is the riskiest investors' behaviour which hammers the dynamics of a financial system and hence leads to an unstable economic environment. Examining this collective behaviour will help the researchers, wealth managers, advisors, and companies to gain deeper insights in patterns of investors' behaviour for both individual and market dynamics. By understanding the underlying drivers and implications of herding, policy makers and academics can develop strategies to minimise its adverse effects and leverage its positive aspects for a more resilient and efficient financial system.

1.1 Herding behaviour in crises

The propensity to herd becomes more pronounced during crises. Bikhchandani and Sharma (2001) elucidate that herding gets intensified during crises due to the sudden spread of panic and fear, which undercuts individual decision-making and triggers his reliance on collective response. Institutional investors, too, engage in herding during market downturns and disasters, aggravating asset-price volatility (Nofsinger and Sias,1999). Further, crisis restrict access to authentic information, resulting in irrational decision-making where investors copy others to avoid probable losses (Christie and Huang, 1995). The global financial crisis of 2008 presents a stark example, where herding among investors escalated the housing market bubble and led to its eventual collapse. In the similar fashion, Bouri et al. (2024) observed a noticeable collective reaction in emerging as well as European markets, due to the uncertainty and global disruptions caused by the health crisis (COVID-19). It thus becomes imperative to understand herding behaviour during crises. Therefore, the present study attempts to empirically study herding during various crises namely, COVID-19 (a health crisis), Russia-Ukraine War (a geo-political crisis) and the failure of federal Bank (an economic crisis).

Furthermore, the rise of globalisation has significantly reshaped the international financial landscape, increasing interdependence among nations (Pike and Pollard, 2010). The diminishing physical boundaries between countries emphasise how movements—whether favourable or adverse—in one nation's macroeconomic indicators can quickly lead to fluctuations across interconnected economies. This interconnectedness is known as financial contagion (Chiang et al., 2007). There have been a many prior studies which have established this interconnectedness with regards to herding, particularly with a strong and powerful economy of USA. Luo and Schinckus (2015) found that herding in China is strongly influenced by mimicking behaviour of investors in the US market. Further, herding spillovers have been noticed between blue-chip stocks in the United Kingdom and the USA (Galariotis et al., 2015) and between the US and Asian markets (Zheng et al., 2017). Accordingly, this study aims to understand the impact of an advanced stock market (US) on the emerging market i.e. India.

1.2 Emerging markets and herding

The tendency to herd, particularly stands out in emerging markets, where transparency and efficiency are often limited (Guney et al., 2017). Such markets are likely to exhibit more herding than the developed markets due to their distinct attributes like weak disclosure requirements, loose accounting standards and information asymmetry (Bikchandani and Sharma, 2000). Here, the market participants take investment decisions based on psychological biases and external market indicators (Tan et al., 2008; Chang et al., 2000). Further, macroeconomic uncertainties and regulatory inefficiencies in these economies often escalate herding, affecting stock price movements adversely and increasing systemic risk. Hence, this continues to be an interesting area of research among academicians.

This paper examines the investors' herding behaviour in the Indian stock market during the ten-year period ranging from 2015-2024. To investigate the spillover effect of US market fluctuations on the herding behaviour in Indian stock market, the paper calculates the contagion effect from herding behaviour in US on the herding behaviour in Indian stock market during the period of study. Furthermore, the research paper examines the response of herding behaviour among Indian investors during various crises, each representing a distinct challenge, namely Covid-19 (a health crisis), Russia-Ukraine war (a geo-political crisis) and the Silicon-Valley bank crisis (an economic crisis). The above-mentioned objectives of the proposed study aim to provide in-depth insights about the market temperament during periods of stress. Also, the paper provides a greater understanding about the vulnerability of the Indian financial system during times of constraints.

Behavioural biases, particularly herding, have garnered significant attention from researchers and academicians in recent years. Numerous studies in the field of behavioural finance have evaluated herd behaviour across various regions globally. However, the existing literature suggests that herding can be more prominently observed in emerging markets due to their distinct characteristics (Guney et al., 2017). This paper examines herding in the Indian stock market, which exhibits the characteristic features of an emerging economy. The study investigates investors' behaviour in the Indian stock market during various crises. The findings of this research provide deep insights for effective strategies to mitigate anxiety-driven herd behaviour and promote a more stable and robust financial system. Furthermore, the research methodology employed in this study to measure herding is more effective than that used in most previous studies. The proposed study utilizes Quantile regression (QR) to calculate herding, which divides the entire dataset into various subsets called quantiles. This approach encompasses extreme values and yields more precise results compared to the earlier technique of Least Squares (Alexander, 2008). The contributions of this paper augment the existing literature and assist future researchers in interpreting the complex patterns of herd behaviour, particularly in the context of the Indian stock market.

This paper has been organised as follows: Section 2 presents an organised and meaningful review of the relevant literature. Section 3 elaborates on the data sources and the methodology adopted for this study. Section 4 and 5 elucidate the analysis and inferences drawn based on considered data set. The limitations of the study and the arears for further research have been highlighted in the concluding section.

2. *Review of Literature*

Although, the asset-pricing theories have contributed significantly to the domain of finance, they have failed to explain the irregularities in investment patterns and market bubbles (Ritter,2003). These limitations of traditional theories led to the modern view, which was led by behavioural theorists, who challenged investors' prudence and made room for behaviourism and normalcy in financial decision-making (Statman, 1999). This alternate theory, known as behavioural finance, suggests that investors do not always follow the path of prudence. Their emotions, moods and anxiety tend to govern their financial decision making, especially in situations of uncertainty and ambiguity (Ritter, 2003).

According to this new approach, investors tend to have some behavioural biases which lead them to behave contrary to the fundamentals of finance. They base their investments on their cognitive impulses which lead to imprecise and biased decisions. Such fallacious moves, herding being the most prominent one, give rise to sharp variation in the fundamental and market valuations of stocks (Shrotriya and Kalra, 2020). Herd behaviour refers to the psychological behaviour of investors to follow others for taking financial decisions, disregarding their own wisdom or analysis (Vieira & Pereira, 2015; Li *et al*., 2017). Herding bias has much more far-reaching impact than personal decision-making; it shapes trends, markets, and even societal movements, making it crucial to study it at length for understanding human behaviour and collective phenomena.

2.1 Reasons of herding

Prior literature on herding has classified its main determinants broadly under three heads, namely: psychological, structural/social and informational factors. Cognitive biases, such as the fear of missing out (FOMO) and loss aversion behaviours often lead investors to follow the crowd, often against rational decision-making (Shiller, 2000). Investors, particularly in times of stress and uncertainty base their investments on their cognitive impulses driven by fear and anxiety which leads them to follow the majority in anticipation of perceived safety (Shrotriya and Kalra, 2022). Structural factors, including reputational risks and the pressure to align with benchmarks, particularly among institutional investors, also play a significant role in fostering herding (Bowe and Domuta, 2004). On the informational side, herding arises from information asymmetry and uncertainty. When investors lack complete market data, they often interpret others' actions as indicators of valuable insights (Bikhchandani et al., 1992; Chang et al., 2000). Herding behaviour is especially common during periods of market volatility and crisis, where fear suppresses rationality, and collective sentiment tends to overshadow individual analysis (Christie & Huang, 1995). Financial crises intensify herding tendencies as market uncertainty propels investors to mimic others for perceived safety.

(Bikchandani and Sharma, 2001) distinguish rational herding from irrational herding. In spurious or rational herding, investors facing similar problems take similar decisions based on similar available information. Rational herding theory posits that even logically minded investors may follow the crowd if they believe others possess better information (Banerjee, 1992). This has been termed as *informational cascades* where investors perceive others' decisions as signals of superior information. While rational herding can lead to alignment of price with market fundamentals, irrational or intentional herding is capable of deviating prices from intrinsic values, resulting in increased volatility (Bikchandani and Sharma, 1992). The rise of technology, which facilitates the rapid spread of trends, has further amplified herding tendencies, underscoring their importance in understanding market dynamics and investor behaviour. (Tao Chen, 2013) observed that crowd behaviour is more apparently visible in developed markets. This is so because these economies provide the perfect environment to process and disseminate financial information and thereby facilitate collective response swiftly. Furthermore, herd behaviour is observed in all Asian markets and all advanced stock markets (Chiang & Zheng, 2010). Herding tendency is more visibly observed in Confucian and less mature countries because of their distinctive characteristics like inefficient governance, loose accounting standards, weak disclosure requirements etc.

2.2 Crisis and herding

Herding is particularly prevalent during times of uncertainty because of elevated fear and negativity. Christie and Huang (1995) argued that investors tend to flock together and trade collectively in response to extraordinary price fluctuations. During market volatility, perceived collective wisdom becomes more influential than individual analysis and market participants are motivated to follow the herd. Similarly, Vo and Phan (2017) emphasized that stock market investors tended to divest from the same stocks simultaneously and shift toward safer assets when returns turned negative. Herding from foreign institutional investors increases during crisis, with herding percentages in the range of 17-20% as compared to pre- crisis (Bowe and Domuta, 2004). Researchers have also identified statistically significant herding behaviour during major market crashes, including the Mexican peso crisis (Chiang and Zheng, 2010), the dot-com bubble (Litimi et al., 2016), the Asian financial crisis (Bowe and Domuta, 2004; Demirer et al., 2014; Zheng et al., 2017), and the global financial meltdown (Chong et al., 2017; Litimi, 2017). However, contrasting findings have been reported. Stavroyiannis and Babalos (2017) found no evidence of herding during periods of turbulence in the U.S. equity market. Similarly, Shrotryia and Kalra (2019) presented insignificant results regarding Indian investors' herding behaviour during the 2008 financial crisis. These mixed findings on the relationship between market turbulence and herding behaviour make it more significant to dig deeper into the domain.

2.3 Statistical methods used to identify herding

Past researchers have used a variety of empirical techniques to identify and measure herding. In international capital markets, flocking behaviour has been extensively examined within stock markets, using two main categories of statistical models. Investor-oriented models focus on analysing trade or transaction data from individual investors and are primarily applied to developed stock markets (Lakonishok et al., 1992; Nofsinger and Sias, 1999; Alda and Ferruz, 2016). On the other hand, the return- based models which study the deviation of individual return from the market return are more suitable for examining emerging (Tan et al., 2008; Lao and Singh, 2011; Yao et al., 2014; Indars et al., 2019) and frontier stock markets (Vo and Phan, 2017, 2019). Among the return-based tools, the most prominent and extensively applied technique is the cross-sectional standard deviation (CSSD) formulated by Christie and Huang (1995). After a few years, this technique was further developed by Chang et al. (2000) and was replaced by a more sophisticated model termed as the cross-sectional absolute deviation (CSAD). (Tao Chen, 2013) observed that for individual stock returns, herding could be significantly and accurately measured by CSAD and Huang and Salmon as compared to the linear model measured by Christei and Huang. Lately, machine learning and network-based models have emerged as a significant tool to identify herding through complex patterns in financial and social network data.

3 Research methodology

This paper intends to examine the herding behaviour in the Indian stock markets during the extended period of 10 years. It further evaluates herding during different selected crises namely, COVID-19 (a health crisis), Russia-Ukraine War (a geo-political crisis) and the failure of Silicon Valley bank (an economic crisis). The paper also analyses the impact of fluctuations in US stock market fluctuations on herding behaviour in the Indian financial market.

Data collection

The proposed study includes daily data of the closing value of Nifty 50 index and S&P 500 index. The data is collected for a period of 10 years ranging from 2015 to 2024 using the Bloomberg database. To collect the data, financial year has been considered. Hence, the period of data ranges from 1st April, 2015 till 31st March, 2024.The study will gauge herd bias during the full sample period as well as during periods of turbulence (COVID-19, Ukraine-Russia war and Silicon Valley bank crisis).

Statistical tools for Analysis

This study employed the return-based approach of '*cross-sectional absolute deviation*' (CSAD) discussed by Chang et al. (2000) and Quantile Regression to estimate the herding parameters. This deviation-based method examines the presence of herding behaviour using the consensus return and demonstrates greater robustness than the earlier method, i.e., '*cross-sectional standard deviation*' discussed by Christie and Huang (1995). The absolute deviation model CSAD aims to examine the non-linear relationship between dispersion and squared consensus return, challenging the foundations of the traditional '*capital asset pricing model*'. The model hypothesized by Chang et al. (2000) is as follows:

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

Where, $CSAD_t$ is Cross sectional absolute deviation, $R_{x,t}$ represents return on index x, $R_{m,t}$ represents consensus/ market return, and N is the number of securities in the portfolio. All the abovementioned parameters will be measured for time t.

The least squares model given by Chang *et al.* (2000) is converted into QR specification and will be separately stated for the overall period, as given by equation (2).

$$Q_\tau(\tau/Y_t) = \alpha_\tau + \gamma_{1,\tau}\left|R_{m,t}\right| + \gamma_{2,\tau}R_{m,t}^2 + \varepsilon_{t,\tau} \quad (2)$$

Where, $Q_\tau(\tau/Y_t)$ represents the vector of all the independent variables (nifty return and nifty return square) in equation (2), $\left|R_{m,t}\right|$ represents the absolute value of consensus return, $R_{m,t}^2$ represents the squared value of consensus return, α_τ is the intercept, and $\varepsilon_{t,\tau}$ is the error term. All the parameters are estimated for time *t* and quantile τ. Although the traditional theories provide that return deviation is a linear and increasing function of market/consensus return, yet the return dispersions weaken and such relation tends to show non-linearity during periods of high price fluctuations (Tan *et al.,* 2008; Gebka and Wohar, 2013). Therefore, significant and negative coefficients of the non-linear term $(\gamma_{2,\tau})$ represents the presence of herding behaviour in the stock market.

Further, the global market impact (or the US market impact) is also incorporated to explain the inter-linkages between the US stock market fluctuations and the Indian stock markets using an improved statistical approach proposed by Luo and Schinckus (2015), represented below equation (3).

$$Q_\tau(\tau/Y_t) = \alpha_\tau + \gamma_{1,\tau}\left|R_{m,t}\right| + \gamma_{2,\tau}R_{m,t}^2 + \gamma_{3,\tau}R_{m,US,t}^2 + \gamma_{4,\tau}CSAD_{US,t} + \varepsilon_{t,\tau} \quad (3)$$

where, $R_{m,US,t}^2$ represents the squared value of the US market return, and $CSAD_{US,t}$ indicates the '*cross sectional absolute deviation*' for the US market represented by S&P 500 index. A significantly negative value of $\gamma_{2,\tau}$ indicates the presence of herd behaviour in the stock market whereas a substantially positive $\gamma_{4,\tau}$ represents that herding in Indian stock market is affected from the herding behaviour in the US stock market. A significant and negative value of $\gamma_{3,\tau}$ significantly ensures that the stock market fluctuations in US stock market impact the herd activity in Indian stock market. All the included parameters are measured for time *t* and quantile τ.

To evaluate the impact of crises situations namely COVID-19, Russia-Ukraine War and Silicon Valley Bank failure, the study will make use of dummy regression specifications (equation 4), where the dummy variable will assume value 1 during such crisis periods, otherwise 0. For the health (Covid-19) crisis, the dummy will take value 1 from 31st December 2019 till 30th June 2020 (Shrotriya and Kalra, 2019) and 0 otherwise. Similarly, for the geo-political (Russia-Ukraine war) crisis, the dummy assumes unity for the period from 24th February 2022 till 31st March,2024 (House of Commons Library, UK Parliament). Prior to the aforesaid period, it will take value 0. Furthermore, the dummy takes value 1 for the duration 8th March 2023 till 27th March 2023 (ET-BFSI) and otherwise 0 for the economic (Silicon Valley bank) crisis. Herding behaviour during the three crises periods will be calculated using the following equation:

$$Q_\tau(\tau/Y_t) = \alpha_\tau + \gamma_{1,\tau}\left|R_{m,t}\right| + \gamma_{2,\tau}R_{m,t}^2 + d_c\gamma_{3,\tau}R_{m,t}^2 + \varepsilon_{t,\tau} \quad (4)$$

A significantly negative parameter γ3; τ is suggestive of strong herding during crisis.

4. Data analysis and interpretation

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Herding behaviour in Indian stock market during normal conditions (From 2015-2024)

The quantile regression was applied on the collected daily data with the '*cross-sectional absolute deviation*' as the dependent variable and Nifty Index returns (both linear and square) as independent variables. Table 1 reported the results of quantile regression:

Table 1: Quantile regression analysis with Cross sectional absolute deviation for identifying herding behaviour

Dependent variable	Independent variable	Quantile	Coefficient	T stats (p value)
Cross sectional absolute deviation	Nifty return	0.1	0.176	7.068** (0.000)
		0.2	0.169	9.946** (0.000)
		0.3	0.200	11.618** (0.000)
		0.4	0.213	13.735** (0.000)
		0.5	0.217	3.922** (0.000)
		0.6	0.232	8.645** (0.000)
		0.7	0.239	3.424** (0.000)
		0.8	0.224	4.351** (0.000)
		0.9	0.190	1.367 (0.171)
	Nifty return Square	0.1	0.457	1.022 (0.306)
		0.2	0.903	7.810** (0.000)
		0.3	0.644	5.459** (0.000)
		0.4	0.521	4.748** (0.000)
		0.5	0.836	0.418 (0.675)
		0.6	1.102	1.929 (0.053)
		0.7	1.742	0.690 (0.490)
		0.8	2.850	2.052** (0.040)
		0.9	5.566	1.254 (0.209)
	Intercept	0.1	0.006	47.759** (0.000)
		0.2	0.007	67.836** (0.000)
		0.3	0.008	74.358** (0.000)
		0.4	0.008	81.511** (0.000)
		0.5	0.009	43.918** (0.000)
		0.6	0.010	69.288** (0.000)
		0.7	0.010	40.634** (0.000)
		0.8	0.011	46.448** (0.000)
		0.9	0.013	26.262** (0.000)

The above table reported the results of quantile regression analysis to identify the herding behavior of the investors in Indian stock market during the overall period of study (2015-2024). The results reported that CSAD tends to increase with the increase in Nifty returns as indicated by positive coefficients in the table, indicating the absence of potential herding behavior during periods of market movement. The significant t statistics at most of the quantiles indicates a strong relationship between Nifty returns and CSAD except at the 0.9 quantile. Similarly in case of the impact of on nifty return square, the results indicate the positive response of CSAD especially at higher quantiles. However, the response of CSAD to nifty returns square at lower quantiles are not significant. The results indicates that higher Nifty returns (both linear and non-linear) lead to the increase in cross-sectional absolute deviation, particularly at higher quantiles, suggesting the absence of herding behavior, also in case with extreme market moves at higher quantile levels. The Nifty returns (squared term) further validate the reverse herding activities at high market conditions, emphasizing the role of extreme market movements in influencing investor behavior.

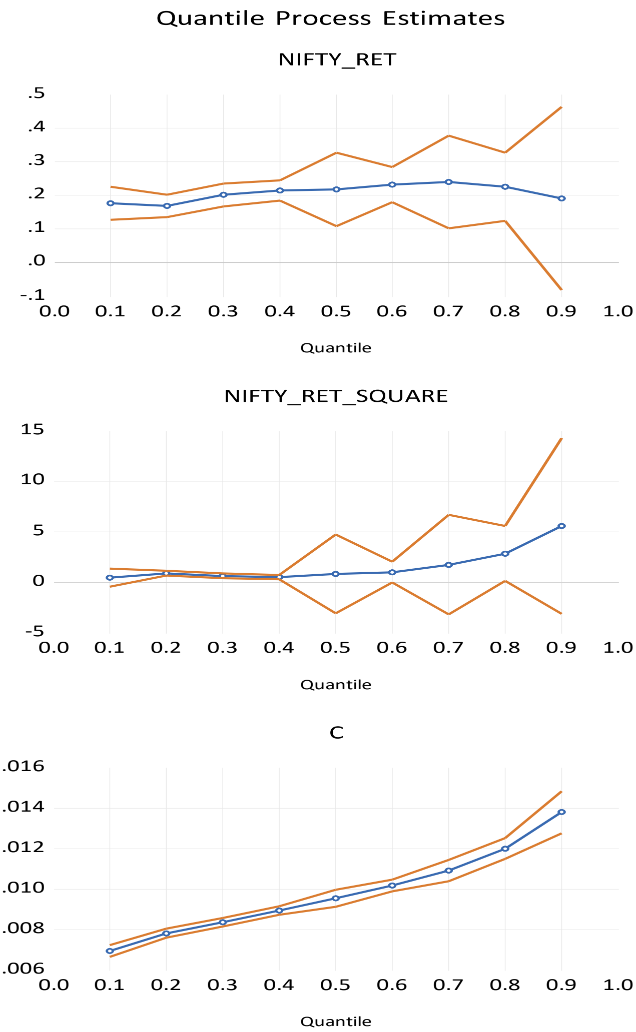

Figure 1: Quantile regression results for herding behaviour in Indian stock market

Table2: Slope equality test and Symmetric Quantiles Test

Test Summary	Chi-Sq. Statistic	Chi-Sq. d.f.	Prob.
Wald Test (Slope equality test)	51.129	4	0.000
Wald Test (Symmetric Quantiles Test)	16.636	3	0.000

Table 2 reports the results of slope equality test and symmetric quantile test to examine the hypotheses of slope equality and symmetric quantiles in the responses of CSAD to the market returns. The result of the slope equality test indicates the presence of unequal slopes of the responses of the CSAD to the market returns at different quantiles (Wald statistics = 51.129, p value = 0.000). The slope is found to increase with quantiles in case of nifty return squares indicating the absolute deviation are higher at higher quantiles indicating that the market is not following heading behaviour in case of high CSAD values. On the other side, the result of symmetric quantile test also supports the presence of asymmetry in the quantile behaviour of the CSAD to the market returns (Wald statistics = 16.636, p value = 0.000). The result indicates significant differences in the symmetric quantiles across groups providing strong evidence against the null hypothesis of equality among the quantiles. Thus, the study concludes the existence of significant differences in the slopes and quantiles being tested.

Study of contagion effect of Herding in the US market on herding behaviour in Indian stock market

The contagion effect refers to the influence that the US market (represented by its cross-sectional absolute deviation, CSAD) has on the Nifty market's investor behaviour, specifically in terms of herding. This effect is observed by analysing the impact of CSAD (US) on the Nifty CSAD across different quantiles. The CSAD (US) coefficients are positive across all quantiles, indicating that increases in market deviation in the US are associated with increases in deviation within the Nifty market. This implies that when US markets experience divergence from typical behaviour (possibly due to unexpected news or shocks), it can lead to similar divergence in the Nifty market, suggesting synchronized behaviour or herding. The coefficients start at 0.053 in the 0.1 quantile and increase to 0.432 in the 0.9 quantile. This pattern suggests that the contagion effect from the US market intensifies as market conditions become more extreme. When the market is in extreme state, whether bullish or bearish, the influence of US market trends on local (Indian) investor behaviour becomes more pronounced. The statistical significance of these coefficients across all quantiles (all p-values ≤ 0.049) indicates a strong and consistent contagion effect. Even at the lower quantiles, which represent more stable market phases, the influence from the US market remains significant. During periods of market stress or volatility, investors in the Nifty market may look up to the US markets for cues, thereby aligning their investment strategies with perceived global trends. This leads to herding behaviour driven by international market movements, particularly during extreme market conditions. In summary, the contagion effect signifies that local Nifty investors are reactive to movements in the US market, with the effect becoming more potent during extreme market fluctuations. This highlights the intertwined nature of global financial markets and the necessity for global awareness in investment strategies.

Table 3: Quantile regression analysis with CSAD for identifying herding behaviour and contagion effect from US CSAD

Dependent variable	**Independent variable**	**Quantile**	**Coefficient**	**T stats (p value)**
		0.1	0.170	6.197** (0.000)
		0.2	0.174	11.067** (0.000)
		0.3	0.191	11.081** (0.000)
	Nifty return	0.4	0.197	12.044** (0.000)
		0.5	0.191	4.181** (0.000)
		0.6	0.199	7.237** (0.000)
		0.7	0.213	3.314** (0.000)
		0.8	0.190	3.929** (0.000)
		0.9	0.158	1.700 (0.089)

Cross sectional absolute deviation	Nifty return Square	0.1	0.329	0.662 (0.507)
		0.2	0.741	6.452** (0.000)
		0.3	0.577	4.717** (0.000)
		0.4	0.404	3.408** (0.000)
		0.5	1.214	0.835 (0.403)
		0.6	1.142	2.190** (0.028)
		0.7	1.092	0.492 (0.622)
		0.8	2.541	1.923** (0.054)
		0.9	3.914	1.268 (0.204)
	CSAD US	0.1	0.053	1.964** (0.049)
		0.2	0.061	3.817** (0.000)
		0.3	0.068	2.662** (0.007)
		0.4	0.116	4.103** (0.000)
		0.5	0.153	5.721** (0.000)
		0.6	0.173	6.969** (0.000)
		0.7	0.217	3.956** (0.000)
		0.8	0.313	8.202** (0.000)
		0.9	0.432	6.381** (0.000)
	Intercept	0.1	0.006	21.780** (0.00)
		0.2	0.007	40.60** (0.000)
		0.3	0.007	36.183** (0.000)
		0.4	0.008	35.416** (0.000)
		0.5	0.008	35.416** (0.000)
		0.6	0.008	42.498** (0.000)
		0.7	0.009	24.138** (0.000)
		0.8	0.009	27.231** (0.000)
		0.9	0.010	19.407** (0.000)

The results of quantile regression analysis (Table 3) to identify the herding behaviour of investors in the Indian stock market along with the contagion effect from the US markets signify a strong and positive correlation. Though, the earlier results observed reverse herding behaviour of investors in Indian stock market during the overall period; However, a strong contagion effect is observed from the US markets absolute deviations as reflected by the positive significant coefficient of CSAD to the CSAD US at different quantiles. In case of the contagion effects, the positive and significant slope coefficients, increases across quantiles (highest at the 0.9 quantile, 0.432), strongly representing contagion effect from the U.S. market is stronger during more extreme market conditions. The results conclude powerful response of CSAD to the US market deviations depicting the potential influence of US market movements on local investor behaviour. The impact of US market deviations also represents significant contagion across all quantiles, with higher effects during extreme market conditions.

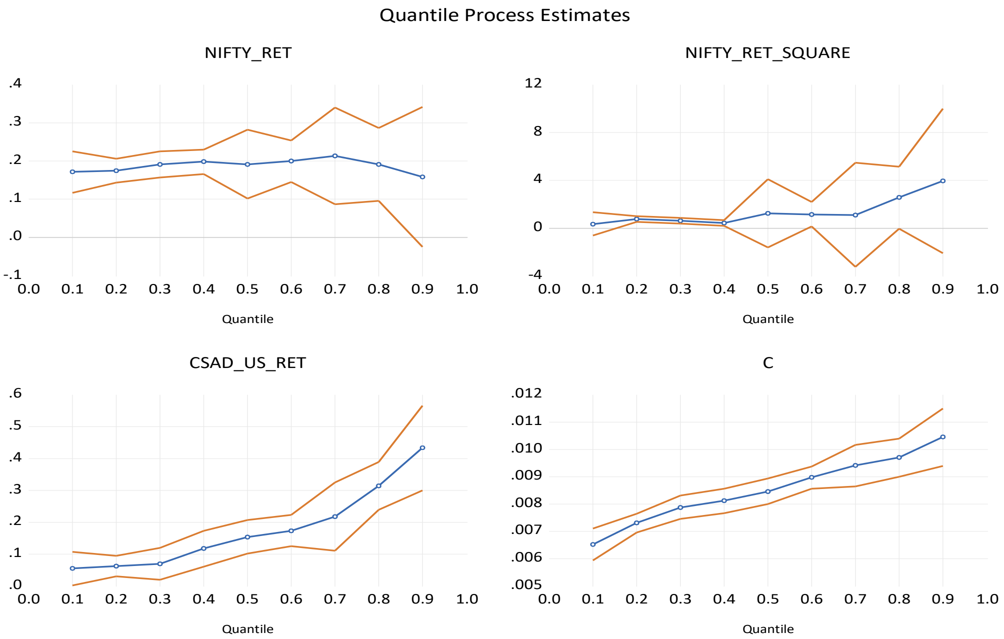

Figure 2: Quantile regression results for herding behaviour in Indian stock market as a result of US stock market fluctuations

Table 4: Slope equality test and Symmetric Quantiles Test

Test Summary	Chi-Sq. Statistic	Chi-Sq. d.f.	Prob.
Wald Test (Slope equality test)	64.005	6	0.000
Wald Test (Symmetric quantiles test)	13.178	4	0.010

The results of slope equality test and symmetric quantile test significantly support the unequal slope and asymmetric quantiles in the responses of CSAD to the US market absolute deviations (Table 4). The result of the slope equality test indicates the presence of unequal slopes of the responses of the CSAD to the US market absolute returns at different quantiles (Wald statistics = 64.005, p value = 0.000). The quantile slope is found to increase with quantiles in case of US market absolute return indicating the CSAD in India responds higher at higher quantiles indicating the presence of strong contagion effects of investors CSAD in India to the US market absolute deviations. The results of symmetric quantile test also support the presence of asymmetry in the quantile behaviour of the CSAD India to the US market absolute deviations (Wald statistics = 13.178, p value = 0.000). The result concludes the presence of significant positive impact (contagion effect) of the absolute deviations in US market on the CSAD in India.

Herding behaviour in stock market during crises

During periods of turbulence, such as health, economic or geo-political crisis, herding behavior may exist in the stock markets, due to the uncertainty and fear among investors. The investors are expected to have a tendency to follow the actions of others, leading to sharp declines and market fluctuations as a result of negative news and sentiment. During adverse times, investor behavior gets influenced by the market behavior rather than the stock fundamentals, creating market volatility. Ruangwises et al. (2023) explains how social media sentiments leads to herd behavior, causing investors to follow the market patterns in stock markets. Liu et al. (2021) observed that the high panic selling in the stock market due to pandemic news, creating fear of the unknown and a herd mentality. The investors behaviour creates feedback loops of declining stock prices. Such behaviors highlight the critical role of psychological factors in investment decision-making during crises periods. The study examines the herd behaviour of investors in Indian stock market due to three recent crises namely COVID-19 pandemic (health crisis), Russia-Ukraine war (geo-political crisis) and Silicon Valley bank crises in US (an economic crisis), with the help of quantile regression model with CSAD in India as dependent variable and by including the interaction dummy (dummy of crises * market return square) as an independent variable. The coefficient of the interaction dummy, if found negative and significant ensures the herd behaviour in the stock markets. Table 5 reported the results of the quantile regression for different selected crises.

Table 5: Herd behaviour of investors in crises period

Dependent variable	**Independent variable**	**Quantile**	**Covid Pandemic Coefficient (p value)**	**Russia-Ukraine war Coefficient (p value)**	**Bank Crises Coefficient (p value)**
Cross sectional absolute Deviation (India)	Nifty return	0.1	0.187 (0.00)	0.210(0.00)	0.175(0.000)
		0.2	0.196(0.00)	0.119(0.00)	0.171(0.000)
		0.3	0.238(0.00)	0.224(0.00)	0.201(0.000)
		0.4	0.247(0.00)	0.230(0.00)	0.214(0.000)
		0.5	0.255(0.00)	0.242(0.00)	0.219(0.000)
		0.6	0.266(0.00)	0.262(0.00)	0.231(0.000)
		0.7	0.277(0.00)	0.257(0.004)	0.243(0.000)
		0.8	0.292(0.001)	0.238(0.001)	0.224(0.000)
		0.9	0.216(0.106)	0.238(0.048)	0.190(0.171)
	Nifty return Square	0.1	-0.090(0.920)	0.034(0.94)	0.457(0.3110
		0.2	-0.478 (0.62)	0.687(0.00)	0.883(0.000)
		0.3	-1.404(0.16)	0.479(0.00)	0.641(0.000)
		0.4	-1.782(0.18)	0.405(0.001)	0.517(0.000)
		0.5	-1.286(0.66)	0.989(0.07)	0.804(0,686)
		0.6	-0.996(0.72)	0.658(0.21)	1.015(0.052)
		0.7	-0.642(0.48)	1.441(0.56)	1.679(0.505)
		0.8	-0.980(0.50)	2.978(0.07)	2.850(0.039)
		0.9	2.195(0.50)	4.566(0.25)	5.566(0.209)
	Herding behaviour in selected Crises	0.1	0.402(0.46)	-6.827(0.15)	0.688(0.691)
		0.2	1.184(0.13)	-5.855(0.001)	-4.654(0.026)
		0.3	1.784(0.04)	-5.923(0.026)	-12.762(0.07)
		0.4	2.063(0.07)	-5.462(0.001)	-18.266(0.02)
		0.5	2.118(0.32)	-4.160(0.030)	-26.047(0.00)
		0.6	1.608(0.45)	-4.857(0.002)	-18.079(0.00)
		0.7	2.899(0.001)	-5.298(0.000)	-22.710(0.00)
		0.8	4.569(0.16)	-6.217(0.000)	-27.611(0.00)
		0.9	5.05(0.15)	-8.507(0.000)	-36.037(0.00)

	Intercept	0.1	0.006(0.00)	0.006(0.000)	0.006(0.000)
		0.2	0.007(0.00)	0.007(0.000)	0.007(0.000)
		0.3	0.008(0.00)	0.008(0.000)	0.008(0.000)
		0.4	0.008(0.00)	0.008(0.000)	0.008(0.000)
		0.5	0.009(0.00)	0.009(0.000)	0.009(0.000)
		0.6	0.010(0.00)	0.010(0.000)	0.010(0.000)
		0.7	0.010(0.00)	0.010(0.000)	0.010(0.000)
		0.8	0.011(0.00)	0.011(0.000)	0.011(0.000)
		0.9	0.013(0.00)	0.013(0.000)	0.013(0.000)

Although, the results of the quantile regression model representing the herd behavior in the stock market as the coefficients of the Nifty return square are found to be negative, however most of the coefficient are statistically insignificant. At the same time, the coefficients of the interaction dummy are found positive and significant at higher quantiles, representing that the investors CSAD increases at higher quantiles of the interaction dummy. In other words, the deviation from the market return increases in the Indian stock market at higher quartiles of the interaction dummy. The just opposite results are observed in Russia Ukraine War, where the coefficients of interaction dummy are found to be negative and statistically significant at different quantiles (Table 5). The significant herd behaviour, is thus concluded in the study, during the Russia Ukraine War. The results indicating that the interaction dummy has a negative and statistically significant coefficient during the Russia-Ukraine War suggest that the herding behavior observed in this context differs from expectations or findings seen in previous crises, like the COVID-19 pandemic. In this case, a negative coefficient implies that as the war progressed, rather than seeing a collective move towards panic selling, investors may have been more discerning, potentially opting to retreat from the market altogether or selectively investing based on available information and risk assessments. The statistical significance at different quantiles indicates that this herding behavior is consistent across various levels of market sentiment and can be generalized to different investor reactions during the crisis. This could reflect a heightened sensitivity to geopolitical risks and an overall strategy shift, where investors prioritized safety over collective action, leading to more cautious behavior in response to the uncertainties created by the conflict. Consequently, the conclusion of significant herding behavior during the Russia-Ukraine War suggests that investors did not blindly follow market trends but rather acted based on strategic considerations influenced by the war's developments. Such findings highlight the complexities of investor psychology and decision-making in response to varying types of crises.

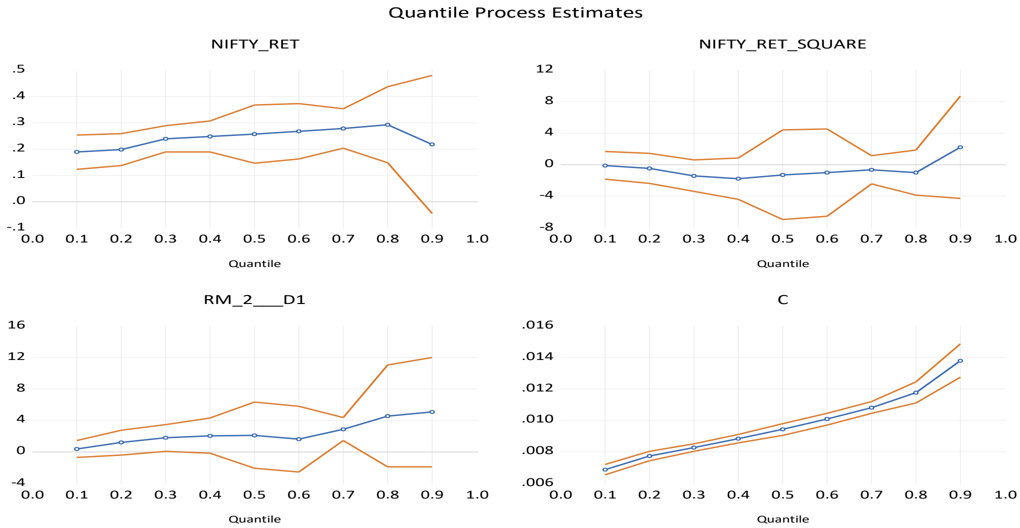

Figure 3: Quantile regression results for herding behaviour in Indian stock market during covid 19 crises

Russia-Ukraine War

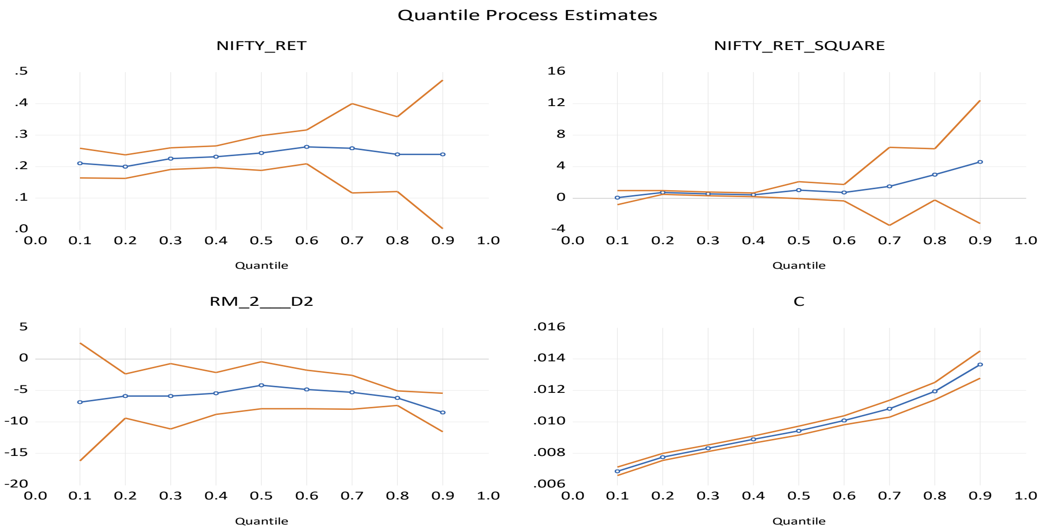

Figure 4: Quantile regression results for herding behaviour in Indian stock market during Russia-Ukraine war

Silicon Valley Bank Crises

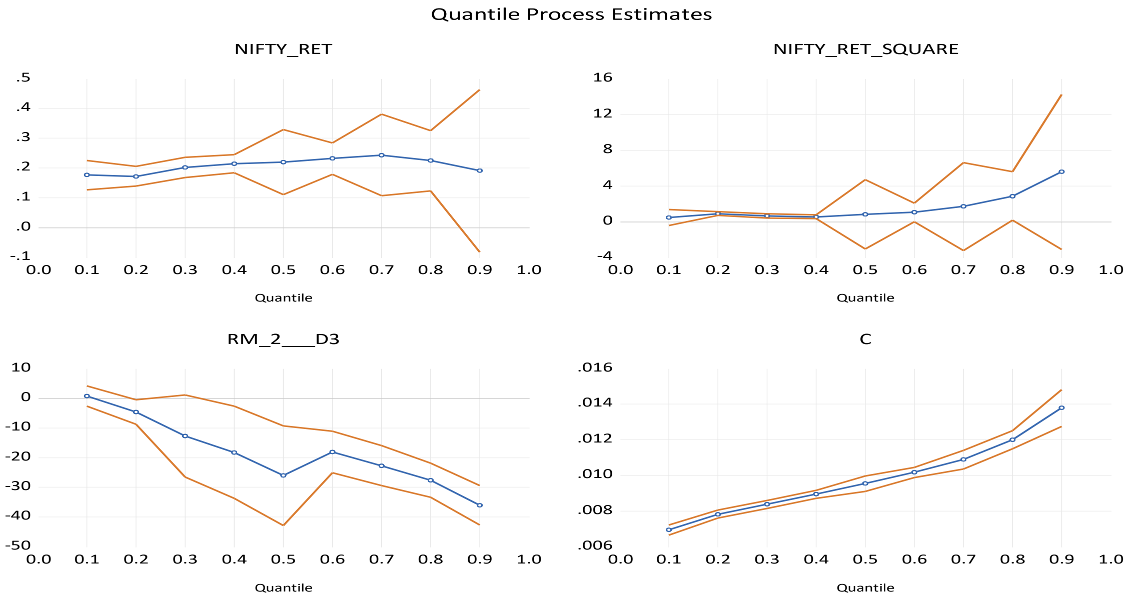

Figure 5: Quantile regression results for herding behaviour in Indian stock market during Silicon Valley Bank crises

Table 6: Slope equality test and symmetric quantiles test for crises period

	Slope Equality Test **Chi Sq Stats (p value)**	**Symmetric Quantiles Test** **Chi Sq Stats (p value)**
Covid crises	87.123 (0.000)	13.483 (0.019)
Russia-Ukraine war	45.251 (0.000)	17.589 (0.001)
Bank Crises	64.580 (0.000)	20.385 (0.000)

The results of slope equality test and symmetric quantile test significantly support the unequal slope and asymmetric quantiles in the responses of CSAD to the herding behaviour in the Indian stock market during the selected crises period. The result of the slope equality test indicates the presence of unequal slopes of the responses to market fluctuations during the all the three selected crises period at different quantiles. The quantile slope is found to both decline (in bank crises) and increases in Covid and Russia War crises, representing the unequal responses of investors in the stock market to the stock market fluctuations. Similarly, the results of symmetric quantile test also support the presence of asymmetry in the quantile behaviour of the CSAD India to the stock market fluctuations in the market crises.

5. Discussion and conclusion

The theory of behavioral finance, based on investor psychology and sentiments presumes presence of herding during most times. However, the existing literature has different findings in different stock markets. This paper found that the Indian stock market does not exhibit significant herding behavior during normal periods, however, strong evidence is found for herding behavior during periods of market crisis. This trend is also reported by the Patel, S. and K, A., 2023, Mishra, P., & Yadav, R. (2022) and Kumari and Sharma (2023) etc. Patel, S. and K, A., 2023 reported that during the 2020 COVID-19 pandemic, significant increase in herding behavior was found among Indian investors, due to the extreme uncertainty and fear, which drives investors to follow the crowd, seeking comfort in numbers. Mishra, P., & Yadav, R. (2022), found significant herding tendencies during major economic downturns or unexpected geopolitical events, as such periods trigger the investors emotionally and psychologically and overpowers their rational decision-making, leading them towards a herd mentality as they attempt to preserve capital and mitigate losses. Herding in Indian context is not uniform across all sectors, instead, it is more prevalent in sectors that are already deemed to be volatile or are directly impacted by the crises at hand, such as technology or banking during economic stress from global events (Kumari and Sharma, 2023). This sector-specific herding highlights the complexity of investor behavior, indicating that while Indian markets may not typically exhibit herding, crises catalyze a shift towards collective movement. Such insights are crucial for policymakers and financial analysts as they develop strategies to manage market stability. The regulatory frameworks can be strengthened to reduce the influence of panic-induced herding, proposing that investor education and awareness can mitigate such phenomena (Gupta and Basu, 2023). Overall, the findings of the paper represent the conditional nature of herding in the Indian stock market. This nuanced understanding aids in creating robust models for predicting market behavior and can be pivotal for investors looking to navigate the complexities of financial crises with greater understanding.

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