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Post-COVID Investor Psychology: Evidence From Loss Aversion, Overconfidence, And Herding In Indian Markets

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Abstract:

The COVID-19 pandemic created unprecedented market uncertainty, providing a unique setting to study investor psychology. The crisis led investors to make emotional rather than rational decisions, reflected through behavioural biases such as loss aversion, overconfidence, and herding. This study examines these behavioural aspects among Indian investors in the post-COVID-19 period by combining market-based measures and Google Trends data as behavioural proxies. Furthermore, financial decision making often involves emotional biases that influence investor judgment and risk perception. Hence, this study explores how behavioural biases such as loss aversion, overconfidence, and herding varied across pre- and post-COVID-19 periods.
The objective is to determine whether the outbreak changed rational investor behaviour in the Indian market. The study relies on secondary data from the National Stock Exchange (NSE) and Google Trends for the period January 2019 to December 2021, covering both pre- and post-pandemic phases. Loss aversion is measured using weekly market returns of the Nifty indices to examine asymmetric reactions to gains and losses. Overconfidence is measured using Abnormal Trading Volume (ATV) derived from weekly market data of the Mid-Cap and Small-Cap indices. Herding behaviour is assessed using the Cross-Sectional Absolute Deviation (CSAD) approach, which identifies the degree to which individual stock returns move together rather than independently. The empirical analysis involves regression models to test the relationship between investor attention (Google search volume) and market behaviour (CSAD, ATV, and return asymmetry).
The study hypothesises that:
(H1) Investors show Imbalanced reaction to gains and losses, responding more strongly to losses than to gains of similar extend, indicating the presence of loss aversion.
(H2) An increase in ATV is positively associated with subsequent market volatility, indicating that higher ATV reflects overconfident trading behaviour among investors.
(H3) Cross-sectional dispersion in stock returns has reduced during periods of extreme market movements, indicating that investors tend to follow collective market behaviour rather than individual assessment.
The expected findings suggest that the health shock intensified behavioural biases, with investors showing heightened loss aversion, increased trading driven by overconfidence, and stronger herding tendencies during periods of market stress. The results are expected to provide insights into how investors panic or overreact during crises, offering implications for behavioural finance, market regulation, and investment strategy formulation. In conclusion, this research contributes to the broader field of behavioural finance by empirically examining how the COVID-19 pandemic influenced investor decision-making patterns in India through measurable behavioural proxies.

Keywords: Behavioural Finance, Loss Aversion, Overconfidence, Herding Behaviour, CSAD, COVID-19, Investor Psychology, Google Search Volume, Indian Stock Market

1.Introduction

The COVID-19 pandemic has deeply transformed the structure and dynamics of global financial markets, creating a natural setting to study how volatility influences investor psychology. Market fluctuations reached extraordinary levels, and investors were driven not only by economic indicators but also by fear, unpredictability, and collective sentiment. India as one of the fastest-growing emerging economies, also experienced remarkable volatility during this period. This unique context provides an important opportunity to examine how psychological tendencies shape investment decisions under stress and instability.

Traditional finance assumes that investors are rational, markets are efficient, and information is freely available. However, real-world evidence consistently deviates from these assumptions. Behavioural finance, an evolving discipline that integrates psychological insights with financial theory, challenges the notion of fully rational investors by emphasising the role of emotions and cognitive biases in financial decision-making. These biases including loss aversion, overconfidence and herding conduct influence not only individual trading patterns but also the broader market dynamics, especially during crises such as the COVID-19 pandemic. In periods of elevated uncertainty, investors tend to rely more on heuristics, leading to deviation from objective decision making.

Loss aversion implies that investors react more strongly to losses than to equivalent gains, a central component of prospect theory (Kahneman & Tversky, 1979). In financial markets, this translates into investors reacting more intensely to downturns than to equivalent upswings. Prior research shows that periods of market instability amplify this effect (Barberis & Huang, 2001; Rakow et al.,2020). By comparing average gains and losses in the pre- and post-COVID periods, the present study examines whether investor's sensitivity to negative returns increased after the crisis. Overconfidence manifests when investors overestimate their knowledge or ability to predict market outcomes (Odean, 1999; Barber & Odean, 2000). Such investors typically engage in excessive market activity, misjudge risks, and overreact to private information. Abnormal trading volume has frequently been used as practical proxy for this bias, as increased trading intensity often signals inflated self-assurance rather than reasoned decision making. (Statman et al.,2006).

The study Investigate whether trading activity, represented through market index volume, significantly changed the post-COVID 19 period, providing insights whether the pandemic Environment amplified or mitigated investor overconfidence across small-cap, mid-cap, large-cap indices. The tendency to follow the crowd on the other hand, tendency of investors to mimic the action of others. It arises when investors follow common trend rather than independent analysis (Christie & Huang, 1995; Cheng, Cheng & Khorana, 2000). This study employs the Cross-Sectional Absolute Deviation (CSAD) model to detect herding by observing the non-linear relationship between overall market return and the dispersion of individual stock returns. Furthermore, recent studies (Da, Engelberg & Gao, 2011) emphasise that Google Search Volume (GSVI) can act as a proxy for investor attention and behaviour. By aligning weekly Google Search activity with market return dispersion. This research examines the evolution of herding tendencies in relation to shifts in collective investor attention before and after the COVID-19 outbreak.

Empirical evidence from emerging markets, particularly India, remains mixed. While some studies (Demirer & Kutan, 2006; Tan et al., 2008) report herding and loss aversion pattern during volatile period, others find that institutional reforms and digital access have moderated such biases. The Indian equity market rapid post-pandemic recovery, coupled with the entry of new retail investors and increased media-driven attention, offers an interesting ground to re-examine these dynamics.

Therefore, this study examines the extent to which cognitive biases specifically loss aversion, overconfidence, and herding shaped investment behaviour in India during the pre-and post-COVID 19 periods (2019-2021). By integrating traditional market indicators such as return and trading volume, and incorporating Google Search Volume Index (GSVI) specifically as a proxy for collective investor attention in the herding model, this paper provides a comprehensive perspective on how investor psychology evolved amid the post-pandemic uncertainty and the subsequent recovery phase.

2.Literature Review

Behavioural finance developed as a critique of the Efficient market hypothesis (Fama,1970), arguing that financial decisions are often influenced by psychological factors rather than pure rationality. Kahneman and Tversky's (1979) Prospect Theory provided the theoretical framework, demonstrated that individuals access gains and losses asymmetrically. This perspective helped explain major cognitive biases loss aversion, overconfidence, and herding that continue to challenge traditional market efficiency assumptions.

Loss aversion describes the tendency to react more intensely to losses than to equivalent gains, which can lead to both risk-averse and risk-seeking tendencies depending on prior outcomes. Barberis and Huang (2001) incorporated this concept into asset pricing models, showing that it contributes to market sluggish response to positive news and overaction to negative developments. Empirical evidences from Goulas and Kontonikas (2014) and Rakow et al. (2020) documented how crises intensify loss aversion, as uncertainty heightens sensitivity to negative information. while Chaudhary et al. (2019) observed that such response are particularly evident in emerging markets, where volatility and information gaps persist.

Overconfidence leads individuals to overrate their judgment and the reliability of their private information. Seminal work by Odean (1998) and Barber and Odean (2001) demonstrated that excessive self-assurance drives frequent trading, ultimately leading lower net returns. Daniel, Hirshleifer, and Subrahmanyam (1998) further connected overconfidence to market momentum and volatility. During periods of market optimism or recovery, trading volume often increases disproportionately to fundamentals. Abnormal Trading Volume (Statman et al., 2006) a common proxy for overconfidence, since excessive activity reflects inflated self-belief rather than superior insight. Post-crisis period, such as the COVID-19 recovery, are particularly relevant for studying this phenomenon due to rising retail participation and easier digital access to trading platforms.

Herding, the collective alignment of market participants' actions, undermines market efficiency by limiting independent decision-making. Christie and Huang (1995) introduced Cross-Sectional Standard Deviation

(CSSD) model to detect herding under stress, later refined by Chang, Cheng, and Khorana (2000) through Cross- Sectional Absolute Deviation (CSAD) approach. These Model identify herding when individual stock returns move in the same direction during volatile market swings. Empirical evidence suggests that herding is more pronounced in emerging economies (Demirer & Kutan, 2006; Tan et al., 2008) where informational asymmetry and investor imitation are stronger.

Recent research has integrated digital data to gauge real-time mood and attention. Da, Engelberg, and Gao (2011) pioneered the use of Google Search Volume Index (GSVI) as a measure of investor attention, revealing its forecasting potential for short-term price and volume fluctuations. Subsequent studies found that spikes in search activity coincide with crowd response to market news, resembling herding patterns. This evolution in data analytics has created new avenues for integrating behavioural insights with market indicators.

Although global evidence on these cognitive biases is extensive, their interaction within India's rapidly evolving financial ecosystem remains underexplored. Particularly aftermath of COVID-19. The crisis driven volatility, coupled with the acceleration of retail participation and digital trading, presents an ideal context for re-assessing investor psychology. This study extends prior literature by jointly examining loss aversion, overconfidence and herding in India. It combines traditional market data with Google Search Volume Index (GSVI) to examine how digital attention metrics relate specifically to herding behaviour, capturing the evolving dynamics of post-pandemic investor psychology.

3.Research Methodology

3.1 Research Design Objectives

This study examines the presence of key behavioural tendencies loss aversion, overconfidence, and herding among Indian investors during the pre-and post-COVID 19 periods. A quantitative, time series design is employing secondary data to assess investor behaviour. Additionally, Google Search Volume (GSV) is included only in the herding analysis to measure investor attention dynamics. The study spans January 2019 to December 202, encompassing both pre-pandemic stability and post-pandemic volatility.

3.2 Data Sources

Market Data

Daily closing prices of Nifty50, Nifty Midcap100, Nifty Smallcap100 indices were sourced from National Stock Exchange (NSE) database. The daily observations were converted into weekly frequency (last trading day of each week) to reduce short-term volatility.

Google Search Volume Data (for Herding Analysis Only)

Weekly Google Trends data were retrieved for the keywords "Nifty50", "Midcap100", and "Smallcap100". The Search Volume Index (SVI), scaled between 0 and 100, was used solely as an attention proxy in the herding model, following Da, Engelberg, and Gao (2011). The GSV data were synchronized by week with the market return dataset to ensure consistency during regression analysis.

3.3 Variables and Measurement Techniques

a. Loss Aversion

Loss Aversion reflects the asymmetric sensitivity of investor to losses relative to gains.

Weekly returns were derived using the formula:

$$R_t = \frac{P_t - P_{t-1}}{P_{t-1}}$$

Where R_t is the return at week t and P_t and P_{t-1} are weekly closing prices.

Two new columns were constructed to separate positive and negative returns:

$$\text{Gain} = \begin{cases} R_t, & \text{if } R_t > 0 \\ 0, & \text{otherwise} \end{cases} \text{and Loss} = \begin{cases} | R_t |, & \text{if } R_t < 0 \\ 0, & \text{otherwise} \end{cases}$$

The Loss aversion Ratio (LAR) was then calculated as:

$$\text{LAR} = \frac{\text{Average Loss}}{\text{Average Gain}}$$

An LAR greater than signifies stronger sensitivity to losses.

To test significant differences between pre- and post-COVID periods, two sample t-tests assuming unequal variances were performed separately for gains and losses in each index.

b. Overconfidence

Overconfidence was proxied using Abnormal Trading Volume (ATV). Following Statman et al. (2006) and Barber & Odean (2001), a higher level of trading activity relative to fundamentals indicates excessive confidence. The mean weekly trading volumes before and after COVID-19 were compared using:

$$t = \frac{\bar{X}_1 - \bar{X}_2}{\sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}}}$$

Where $\bar{X}_1$ and $\bar{X}_2$ are mean trading volumes for the pre -and post-COVID periods s_1^2, s_2^2 are their respective variances.

A statistically substantial increase in mean volume post-COVID implies higher trading activity driven by overconfidence.

c. Herding Behaviour

Herding was examine using the Cross-Sectional Absolute Deviation (CSAD) model (chang, Cheng & Khorana, 2000):

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

The baseline regression model is:

$$CSAD_t = \alpha + \beta_1 | R_{m,t} | + \beta_2 R_{m,t}^2 + \epsilon_t$$

A negative significant β_2 reflects herding, meaning individual return dispersion decrease when market movements become extreme.

To incorporate investor attention, the model was extended with Google Search Volume (GSV) variable as follow:

$$CSAD_t = \alpha + \beta_1 \mid R_{m,t} \mid + \beta_2 R_{m,t}^2 + \beta_3 GSV_t + \epsilon_t$$

Here, GSV_t captures investor attention and collective sentiment, allowing the study to explore whether heightened search activity amplifies herding tendencies.

3.4 Statistical Tools

All statistical analyses were performed using Microsoft Excel (Data Analysis Toolpak). Methods included:

- Calculation of weekly returns, gains, and losses.
- Paired and independent t-test for mean comparison.
- Multiple linear regression CSAD estimations.
- Correlation analysis to examine the relationship between CSAD and GSV

Significance was tested at 1%, 5%, and 10% levels.

3.5 Period Classification

Period	Time Frame	Description
Pre-COVID	Jan 2019–Feb 2020	Market under normal conditions
Post-COVID	Mar 2020–Dec 2021	Period of heightened volatility and behavioural shifts

4.Results and Discussion

4.1 Loss Aversion

The study first examined whether investors displayed asymmetric reaction to gains and losses during the pre- and post-COVID-19 periods. Using weekly returns from the Nifty Small Cap 100, Nifty Mid Cap 100, and Nifty 50 indices, Loss aversion Ratios (LAR) were calculated as the ratio of average losses to average gains.

Index	Period	Avg. Gain	Avg. Loss	LAR
Small Cap	Pre-COVID	0.0076	0.0086	1.128
Small Cap	Post-COVID	0.0098	0.0130	1.320
Mid Cap	Pre-COVID	0.0075	0.0080	1.066
Mid Cap	Post-COVID	0.0097	0.0130	1.341
Large Cap	Pre-COVID	0.0075	0.0080	1.066
Large Cap	Post-COVID	0.0097	0.0130	1.341

Across all three indices, the Loss Aversion Ratio increased post-COVID, indicating that investors reacted more strongly to losses than to equivalent gains after the pandemic. This rise in sensitivity reflects heightened risk aversion and emotional reactivity, consistent with Kahneman and Tversky's (1979) Prospect Theory, which posits that losses loom larger than gains.

The t-test results further support this pattern. For the Small-Cap and Mid-Cap indices, the post-COVID loss means were significantly higher than pre-COVID ($p < 0.05$), while gain-side differences were also significant. This asymmetry suggests that investor became increasingly cautious and loss-sensitive during the volatile post-pandemic period.

These findings align with Barberis, Huang, and Santos (2001) who emphasised that negative market shocks amplify investor pessimism and reduce risk tolerance, particularly in smaller and more volatile market segments.

4.2 Overconfidence

Overconfidence was measured using Abnormal Trading Volume (ATV) as a behavioural proxy. The mean weekly trading volumes during the pre- and post-COVID periods were compared using a two-sample t-test.

Index	Mean (Pre-COVID)	Mean (Post-COVID)	p (One-tailed)	Inference
Small Cap	19.10	19.20	0.099	Not significant
Mid Cap	-0.001	0.008	0.041	Significant increase
Large Cap	20.01	20.07	0.199	Not significant

The results indicate that only the Mid-Cap index exhibited significant evidence of overconfidence post-COVID ($p = 0.041 < 0.05$).

This suggests that mid-cap investors engaged in higher trading activity relative to fundamentals, likely reflecting overreaction and excessive optimism during the recovery phase.

In contrast, large- and small-cap indices showed no statistically significant difference, implying that overconfidence may have been concentrated among mid-tier investors. Large-cap investors likely demonstrated more institutional discipline, whereas small-cap investors may have remained risk-averse or liquidity-constrained.

These findings corroborate Odean (1998) and Barber and Odean (2001), who documented that overconfident investors tend to trade excessively in bullish periods, often reducing net returns.
Similarly, Statman et al. (2006) identified abnormal trading volume as a robust indicator of investor overconfidence, which aligns with the present study's results in the mid-cap segment.

4.3 Herding Behaviour

Herding tendencies were evaluated using the Cross-Sectional Absolute Deviation (CSAD) model proposed by Chang, Cheng, and Khorana (2000), with regressions estimated separately for pre- and post-COVID periods.

Period	R^2	β_1 (Rm)	β_2 (Rm^2)	Significance (p-value)	Interpretation
Pre-COVID	0.099	0.174	-2.280	0.059	Weak evidence of herding
Post-COVID	0.172	0.119	-0.301	0.0004	Stronger herding behaviour

The negative β_2 coefficient in both periods indicates herding tendencies investors moving together during extreme market swings.
However, the effect became stronger and statistically significant post-COVID ($p < 0.01$), suggesting that market participants increasingly followed collective sentiment rather than independent judgment.
This finding supports Christie and Huang (1995) and Chang, Cheng, and Khorana (2000), who observed that during turbulent markets, investors are prone to mimic the crowd, reducing return dispersion.
In India's case, the heightened uncertainty and online information flow during the pandemic likely intensified this collective behaviour.

4.4 Herding and Google Search Volume (Investor Attention)

To explore the interaction between investor attention and herding, the Google Search Volume Index (GSV) was incorporated into the CSAD regression model as an additional explanatory variable:

$$CSAD_t = \alpha + \beta_1 \mid R_{m,t} \mid + \beta_2 R_{m,t}^2 + \beta_3 GSV_t + \varepsilon_t$$

When GSV was included, the following results were observed:

Period	β_3 (GSV)	p-value	R^2	Interpretation
Pre-COVID	-0.00010	0.273	0.130	Weak negative association
Post-COVID	0.00003	0.841	0.173	Weak positive association

Additionally, the correlation between CSAD and GSV was 0.164, indicating a weak but positive link between search intensity and market dispersion.
While β_3 remained statistically insignificant, the positive post-COVID coefficient implies that higher search activity coincided with greater variation in individual behaviour, suggesting that investors relied more on independent online information rather than mimicking others.
This outcome is consistent with Da, Engelberg, and Gao (2011), who demonstrated that Google search activity captures investor attention, not necessarily imitation.
Thus, in the Indian context, digital awareness may have encouraged information-seeking behaviour, reducing collective herding despite heightened market attention.

4.5 Discussion

The empirical findings demonstrate distinct behavioural shifts following the COVID-19 crisis.

- Loss aversion increased substantially across all indices, showing that investors became more risk-averse and emotionally sensitive to losses.
- Overconfidence was evident primarily in the mid-cap segment, reflecting selective optimism and speculative trading during the recovery phase.
- Herding behaviour intensified post-COVID, though moderate, suggesting that collective sentiment guided decisions during market volatility.
- Google Search Volume, while weakly correlated with herding, indicates an evolution toward information-driven rather than imitation-driven behaviour.

Overall, the evidence suggests that investor Psychology during the post-pandemic period was shaped by a complex interaction of fear, attention, and optimism. While uncertainty heightened emotional biases, technological access and online information mitigated uniform herding behaviour, reflecting a gradual maturation of Indian market behaviour.

These findings reinforce behavioural finance literature (Kahneman & Tversky, 1979; Barberis & Huang, 2001; Da et al.,2011) and highlight how crisis-driven uncertainty and digitalisation jointly influence market sentiment and trading dynamics.

5.Conclusion

This study provides empirical evidence on how investor psychology in India evolved before and after the COVID-19 pandemic, focusing on three major behavioural biases loss aversion, overconfidence, and herding. Using data from the Nifty small cap 100, Nifty midcap 100, and Nifty 50 indices, and supplementing with Google Search Volume Index (GSVI) to capture investor attention, the research highlights that the pandemic not only disrupted economic fundamentals but also altered the emotional and cognitive dimensions of investment behaviour.

The results reveal a notable increase in loss aversion following the onset of COVID-19, implying that investors reacted more strongly to losses than to equivalent gains. This is consistent with Prospect theory (Kahneman & Tversky, 1979), which asserts that individuals are more sensitive to losses, particularly in uncertain conditions. The heightened post-pandemic sensitivity suggest that the market downturn and subsequent volatility intensified investors' fear of loss and reduced their willingness to take risk. Such findings support the arguments of Barberis and Huang (2001) and Rakow et al. (2020), who observed that adverse market shocks strengthen emotional responses and influence portfolio decisions.

The analysis of overconfidence reveals that this bias was more pronounced among mid-cap investors during the post-COVID recovery phase. Increased trading volumes, disconnected from fundamentals, indicate that certain investor groups exhibited inflated self-belief and speculative enthusiasm. This behavioural pattern is consistent with Odean (1998) and Barber & Odean (2001), who demonstrated that excessive trading often results from overestimation of personal skill or private information accuracy. Interestingly, this tendency was less evident in large-cap and small-cap indices, possibly due to institutional dominance in large-cap markets and liquidity constraints in smaller ones.

The herding analysis, using the Cross-Sectional Absolute Deviation (CSAD) model, shows stronger and statistically significant herding behaviour during the post-COVID period. The negative non-linear coefficient suggests that as market stress intensified, investors increasingly followed collective trends rather than independent judgment. When Google Search Volume Index (GSVI) was introduced, a weak positive correlation with herding confirmed that higher online search activity was associated with heightened collective attention, though not necessarily with blind imitation. This observation aligns with Da, Engelberg, and Gao (2011) and Preis et al. (2013), highlighting that digital data can capture real-time investor attention and sentiment, influencing market-wide reactions.

Collectively, these findings demonstrate that the pandemic amplified behavioural biases in India's equity markets, though with differing intensities across market segments. While fear and uncertainty heightened loss aversion and herding, the post-crisis optimism contributed to selective overconfidence, particularly among mid-cap traders. This dual behavioural shift underlines the psychological complexity of investors in emerging markets, where structural reforms, digitalisation, and increased retail participation interact with traditional emotional tendencies.

Policy and Practical Implications

1. Investor Awareness:
   Regulators such as SEBI should incorporate behavioural insights into investor education programmes. Emphasising the dangers of overconfidence and herd-following during market rallies can help investors maintain discipline.
2. Crisis Communication:
   Transparent communication from financial authorities during market turbulence can reduce panic and herd-driven decisions, mitigating market overreactions.
3. Behavioural Indicators in Regulation:
   Incorporating behavioural data (like abnormal trading volume and GSVI) into monitoring systems could help identify early signs of speculative bubbles or panic-driven trading.
4. Product Innovation:
5. Financial institutions can design risk-managed investment products, such as automatic stop-loss mechanisms or balanced funds, to protect retail investors from bias-driven decisions.
6. Future Research:
   Future studies could incorporate additional sentiment metrics such as Twitter or media sentiment indices and explore cross-country comparisons to understand behavioural convergence in crisis periods.

In conclusion, the COVID-19 pandemic acted as a natural experiment in behavioural finance, revealing how emotional and cognitive biases interact with modern information systems. As India's financial ecosystem becomes more digital and retail-driven, understanding these behavioural shifts is vital for building resilient, informed, and stable markets.

Limitations

Despite offering valuable insights into investor psychology during the COVID-19 period, this study is subject to several important limitations.

First, the analysis is restricted to three broad market indices—Nifty 50, Nifty Mid-Cap 100, and Nifty Small-Cap 100. While these represent major market segments, they do not capture variations across specific industries, firm categories, or sectors that may exhibit different behavioural patterns. Sector-level or firm-level dispersion may reveal more granular behaviour that index-level data cannot fully reflect.

Second, behavioural biases were inferred using market-based proxies such as the Loss Aversion Ratio (LAR), Abnormal Trading Volume (ATV), and the Cross-Sectional Absolute Deviation (CSAD) model, along with Google Search Volume (GSV) as an attention proxy. Although widely used in behavioural finance literature, these indirect measures may not fully capture the underlying cognitive or emotional mechanisms that drive investor behaviour. For example, CSAD detects collective return movement but cannot distinguish rational convergence from true herd behaviour. Similarly, GSV may reflect curiosity, media coverage, or general information-seeking rather than actual trading intentions.

Third, the study relies exclusively on secondary data from 2019 to 2021, a period dominated by COVID-19-specific shocks. This relatively short time frame may limit the ability to observe long-term behavioural adjustments or post-pandemic normalization. Investor behaviour during crises may differ fundamentally from behaviour during extended stable periods, making generalisation difficult.

Fourth, the study does not explicitly control for macroeconomic variables (such as interest rates, inflation, FPI flows, or policy announcements) that may also influence trading behaviour and return dispersion. The exclusion of such variables raises the possibility of omitted-variable bias in the regression models, particularly in the herding analysis.

Fifth, the Google Search Volume Index used in the herding model captures attention only at an aggregate weekly level. It does not differentiate between investor segments (retail vs. institutional) or between informational and behavioural searches, which may dilute the precision of the attention–herding relationship.

Future Research Directions

Future studies can enrich behavioural insights by integrating real-time sentiment indicators such as Twitter sentiment scores, news sentiment indices, or investor surveys to provide more direct psychological validation. Researchers may also consider firm-level or sector-specific CSAD models for deeper granularity. Incorporating macroeconomic controls, expanding the data window beyond the pandemic, and comparing India with other emerging or developed markets can enhance generalisability. Additionally, machine-learning techniques, such as neural-network sentiment models or regime-switching behavioural models, could offer more robust predictions of behavioural shifts during financial crises.

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