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Relationship between Market Sentiment and Retail Investor Actions

Rahul Anand, Dr. Batani Raghavendra Rao

CMS Business School, Faculty of Management Studies, JAIN (Deemed-to-be University), Bengaluru, India

Professor, CMS Business School, Faculty of Management Studies, JAIN (Deemed-to-be University), Bengaluru, India

ABSTRACT: This paper explores how prevailing market sentiment shapes the investment decisions of retail equity investors in India a question that has taken on fresh urgency given the rapid expansion of the Indian retail investor base since 2020. Using a mixed-methods design, the study draws on primary survey data from 210 active retail investors alongside secondary data from NSE India and the Reserve Bank of India. Four sentiment indicators were examined as independent variables India VIX perception, social media sentiment, consumer confidence, and financial news tonality and tested against four behavioural outcomes: herding, panic selling, overconfidence-driven trading, and portfolio decision quality. The analytical toolkit included Pearson correlation, hierarchical multiple regression, one-way ANOVA, and thematic analysis of open-ended responses. India VIX perception emerged as the strongest predictor of herding ($\beta = 0.421$, $p < 0.001$), while financial news sentiment showed the highest correlation with panic selling ($r = 0.603$, $p < 0.001$). Social media sentiment independently predicted trading frequency after controlling for other channels, and consumer confidence consistently reduced the likelihood of adverse behavioural outcomes. Investment experience proved a meaningful moderating variable ($\beta = 0.219$, $p = 0.012$), and all five null hypotheses were rejected. The regression model accounted for 57.3% of variance in herding behaviour (Adj. $R^2 = 0.573$). The findings contribute empirically grounded evidence from the Indian retail context and draw out practical implications for investors, advisors, platforms, and regulators.

KEYWORDS: Market Sentiment, Retail Investor Behaviour, Herding, Behavioural Finance, India VIX, Panic Selling, Social Media Sentiment

I. INTRODUCTION

India's retail equity market has changed almost beyond recognition over the past five years. SEBI data shows that registered retail demat accounts jumped from roughly 4 crore in early 2020 to well over 11 crore by end-2023 a near-tripling of market participation across a period that witnessed the COVID-19 crash, one of the sharpest recoveries in recorded financial history, and the sweeping global monetary tightening of 2022–23. A large proportion of India's current retail investor base therefore entered equity markets during conditions of extraordinary turbulence. The behavioural patterns formed under those circumstances the reflexes, the information habits, the emotional defaults are still very much in play.

At the centre of this paper is the concept of market sentiment: the aggregate emotional orientation of investors toward where prices are headed, which manifests across implied volatility measures, financial news tone, social media chatter, and macroeconomic confidence surveys simultaneously. Sentiment is notoriously difficult to pin down as a research variable precisely because it is diffuse it does not collapse neatly into a single observable number. Yet it keeps appearing in trading data in ways that are hard to explain otherwise, particularly in a market like India where the newest investors are disproportionately young, digitally connected, and reliant on informal information channels.

The behavioural finance literature is rich with studies on sentiment effects, but the overwhelming bulk of it draws on data from the United States and Western Europe markets that differ substantially from India in terms of investor demographics, information asymmetries, and the weight carried by social media and informal networks. Aggregate secondary data also has a fundamental limitation: it cannot tell us what individual investors are actually feeling or how they are interpreting sentiment signals at the point of decision. This study addresses that gap through primary survey data from 210 active retail investors across Indian Tier 1 and Tier 2 cities.

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Four sentiment channels are examined perceptions of India VIX, social media sentiment, consumer confidence, and financial news tonality and their influence on four behavioural outcomes: herding, panic selling, overconfidence-driven trading, and overall portfolio decision quality. The paper also asks whether investment experience moderates these relationships a question with direct relevance for investor education. The central research question, simply stated, is: to what extent does market sentiment systematically drive the investment decisions of Indian retail equity investors, and does time in the market provide any meaningful insulation against those effects?

II. REVIEW OF LITERATURE AND THEORETICAL FRAMEWORK

2.1 Market Sentiment and Asset Pricing

Baker and Wurgler (2006) constructed a composite sentiment index from six market-level proxies and demonstrated that it predicted cross-sectional stock returns particularly for securities that are hard to value and difficult to arbitrage. Their work established that sentiment is a systematic, measurable variable with real pricing consequences, not simply a residual that models cannot explain. The multi-indicator framework adopted in this study follows a similar logic: no single proxy is adequate; sentiment needs to be triangulated. Shiller (2000, 2019) showed in considerable detail how speculative enthusiasm sustained through media narratives and social contagion can hold asset prices at levels disconnected from fundamentals for extended periods, and his later concept of 'narrative economics' is directly relevant to the social media sentiment variable tested here.

The formal theoretical grounding for why sentiment-driven retail trading matters at the market level comes from De Long, Shleifer, Summers, and Waldmann (1990), whose noise trader model demonstrated that noise trader risk is itself an undiversifiable, priced source of risk. Sentiment-driven retail investors can therefore affect prices in systematic, persistent ways even when rational arbitrageurs are present the theoretical mechanism underlying this entire study.

2.2 Retail Investor Behaviour

Barber and Odean (2008) documented attention-driven buying retail investors disproportionately purchase stocks that have recently featured in news coverage or displayed extreme price movement, regardless of whether that signal is positive or negative. Kahneman and Tversky's (1979) Prospect Theory provides the cognitive foundation: losses are weighted approximately twice as heavily as equivalent gains, which predicts that negative sentiment signals will produce stronger and more immediate behavioural responses. Kumar and Lee (2006) found that retail investor buy-sell imbalances are systematically correlated across individuals, with correlated behaviour affecting prices especially in smaller stocks the closest empirical antecedent to the herding variable measured in this study.

2.3 Social Media and Digital Sentiment

Bollen, Mao, and Zeng (2011) showed that mood extracted from Twitter had measurable predictive power over Dow Jones daily returns. Da, Engelberg, and Gao (2015) constructed a retail fear index from Google search volume that predicted negative returns on high-search days. Chen et al. (2014) found pessimistic tone in user-generated Seeking Alpha articles predicted lower future earnings surprises. In the Indian context, Gupta, Goyal, and Kashiramka (2019) adapted the Baker-Wurgler framework and found significant short-run predictive relationships, while Chandra and Kumar (2012) documented correlations between media tone and mutual fund flows among Indian investors. Post-pandemic work by Haroon and Rizvi (2020) provided evidence that COVID-era sentiment shocks triggered herding and panic selling in India, as elsewhere.

2.4 Theoretical Framework

Three frameworks underpin the study. Behavioural Finance Theory (Kahneman & Tversky, 1979; Shleifer, 2000) explains sentiment processing at the individual cognitive level retail investors amplify loss-related cues, over-weight vivid recent events, and gravitate toward social validation under uncertainty. The Noise Trader Model (De Long et al., 1990) scales these dynamics to the market level, explaining why correlated sentiment-driven retail trading produces systematic, non-random price effects. Information Cascade Theory (Bikhchandani, Hirshleifer, & Welch, 1992) explains the mechanism through which social media sentiment produces correlated behaviour: when individuals can observe sufficient peer decisions through digital platforms, following the crowd becomes individually rational even without independent analysis. What digital platforms have changed is the speed and scale algorithmic amplification can collapse into minutes what previously took days.

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III. RESEARCH METHODOLOGY

3.1 Research Design and Scope

A mixed-methods design was adopted, combining quantitative hypothesis testing with qualitative thematic analysis of open-ended responses. The research logic is primarily deductive hypotheses were derived from established theoretical frameworks supplemented by an inductive qualitative strand to capture patterns not anticipated in the hypothesis structure. The strategy is a cross-sectional survey with a retrospective element: respondents reflected on investment decisions made over the preceding twelve months, providing a broader temporal base than a purely contemporaneous snapshot. The study is scoped to retail equity investors actively trading on NSE or BSE with a minimum six-month active investment history, drawn from Tier 1 and Tier 2 Indian cities. Institutional investors, FIIs, and HNIs are excluded.

3.2 Research Hypotheses

- H01: No significant relationship exists between India VIX perception and herding behaviour among retail investors.
- H02: Social media sentiment does not significantly predict retail investor trading frequency.
- H03: Consumer confidence levels do not significantly influence retail investor risk appetite.
- H04: Financial news sentiment has no significant relationship with panic selling propensity.
- H05: Investment experience does not significantly moderate the sentiment-behaviour relationship.

3.3 Data Collection and Variables

Primary data were collected through a structured questionnaire drawn from validated behavioural finance scales, adapted for the Indian context and pre-tested with a pilot group of 20 investors. The final instrument contained 42 closed-ended items across five scales along with five open-ended questions. Sampling combined purposive and snowball techniques; administration used both online (Google Forms) and in-person modes. Of 248 questionnaires distributed, 210 were retained after removing incomplete responses (usable response rate: 84.7%). Secondary data were drawn from NSE India's VIX portal, the RBI Household Survey database (Consumer Confidence Index), and Thomson Reuters News Analytics.

Independent variables: India VIX Perception Score (12-item scale, $\alpha = 0.847$); Social Media Sentiment Score (5-point Likert); Consumer Confidence Perception Score (5-point Likert); Financial News Sentiment Score (5-point Likert). Dependent variables: Herding Behaviour Index ($\alpha = 0.821$); Panic Selling Propensity Index ($\alpha = 0.809$); Overconfidence Trading Index ($\alpha = 0.784$); Portfolio Decision Quality Index ($\alpha = 0.812$). Moderating variable: Investment experience in years (self-reported).

3.4 Analytical Techniques

All quantitative analyses were conducted in IBM SPSS Statistics v26.0, moving from descriptive statistics and Cronbach's Alpha reliability testing through Pearson bivariate correlation to hierarchical multiple regression (demographics in Block 1, sentiment predictors in Block 2) and one-way ANOVA with post-hoc Tukey HSD tests. Moderated regression via the Hayes PROCESS macro (Model 1) tested the experience-moderation hypothesis. Qualitative data from open-ended responses were analysed using Braun and Clarke's (2006) six-phase thematic analysis; inter-rater reliability was assessed via Cohen's Kappa ($\kappa = 0.81$).

IV. DATA ANALYSIS AND RESULTS

4.1 Sample Profile

The 26–35 age cohort is the largest group at 37.6% (n = 79). Combined with the 18–25 cohort (27.6%, n = 58), more than six in ten respondents are under 36 consistent with SEBI's demographic data on post-pandemic market entrants. A particularly notable finding is that 41.4% of respondents identified social media as their primary investment information channel, exceeding financial news portals (29.0%), stockbrokers or advisors (18.1%), and friends or family (11.4%) combined (Table 1).

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Table 1: Demographic Profile of Survey Respondents (N = 210)

Variable	Category	Frequency (n)	Percentage (%)
Age Group	18–25 years	58	27.6%
	26–35 years	79	37.6%
	36–45 years	45	21.4%
	46 years and above	28	13.3%
Gender	Male	142	67.6%
	Female	64	30.5%
Investment Experience	Less than 1 year	42	20.0%
	1–3 years	68	32.4%
	3–5 years	55	26.2%
	More than 5 years	45	21.4%
Primary Info Source	Social media	87	41.4%
	Financial news portals	61	29.0%
	Stockbroker/Advisor	38	18.1%
	Friends/family	24	11.4%

4.2 Descriptive Statistics and Reliability

India VIX Perception (M = 3.42, SD = 0.847) and Financial News Sentiment (M = 3.31, SD = 0.921) scored above the scale midpoint of 3.0, indicating respondents perceived meaningful negative sentiment from both channels during the reference period. Consumer Confidence recorded the lowest mean (M = 2.97, SD = 0.889), marginally below neutral. Among behavioural outcomes, herding registered the highest mean (M = 3.54), followed by panic selling (M = 3.21). The overall instrument Cronbach's Alpha of 0.891 falls in the excellent range; all individual scales exceeded the 0.70 threshold (Table 2).

Table 2: Cronbach's Alpha Reliability of the Research Instrument

Scale	No. of Items	Cronbach's Alpha	Interpretation
Market Sentiment Perception	12	0.847	Good
Herding Behaviour	8	0.821	Good
Panic Selling	6	0.809	Good
Overconfidence Trading	5	0.784	Acceptable
Portfolio Decision Quality	7	0.812	Good
Overall Instrument	38	0.891	Excellent

4.3 Bivariate Correlation Analysis

All correlations are statistically significant at $p < 0.01$ (Table 3). India VIX perception shows the strongest positive association with herding ($r = 0.614$), a large effect by conventional benchmarks. Financial news sentiment is most tightly correlated with panic selling ($r = 0.603$), suggesting that different sentiment channels activate different behavioural responses. Consumer confidence displays consistently negative correlations with herding ($r = −0.312$) and panic selling ($r = −0.394$) indicating that higher macroeconomic confidence functions as a psychological buffer, reducing the likelihood of adverse sentiment-driven decisions.

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Table 3: Correlation Matrix Sentiment Indicators and Investor Behaviour Variables

Variable	India VIX	Social Media	Consumer Conf.	News Sent.	Herding	Panic Selling
India VIX Score	1.00					
Social Media Sentiment	0.432**	1.00				
Consumer Confidence	−0.318**	0.241**	1.00			
News Sentiment	0.489**	0.521**	−0.289**	1.00		
Herding Behaviour	0.614**	0.578**	−0.312**	0.541**	1.00	
Panic Selling	0.587**	0.492**	−0.394**	0.603**	0.689**	1.00
Overconfidence Trading	0.312**	0.461**	0.278**	0.289**	0.341**	0.218**

Note: ** $p < 0.01$ (two-tailed). N = 210.

4.4 Multiple Regression Analysis

Hierarchical multiple regression was run with herding behaviour as the dependent variable demographic controls in Block 1, sentiment predictors in Block 2. The overall model is statistically significant ($F(4, 205) = 71.29$, $p < 0.001$) and explains 57.3% of variance in herding after controlling for demographics (Adj. $R^2 = 0.573$), a notably high proportion for a behavioural study (Table 4).

Table 4: Multiple Regression Coefficients Predicting Herding Behaviour

Predictor Variable	B	Std. Error	Beta (β)	t-value	p-value
(Constant)	0.812	0.214	—	3.795	0.000
India VIX Perception	0.381	0.048	0.421	7.938	0.000**
Social Media Sentiment	0.294	0.052	0.312	5.654	0.000**
Consumer Confidence	−0.187	0.049	−0.198	−3.816	0.000**
News Sentiment	0.243	0.051	0.267	4.765	0.000**

Note: $R^2 = 0.581$; Adj. $R^2 = 0.573$; $F(4, 205) = 71.29$, $p < 0.001$. ** $p < 0.001$.

India VIX Perception is the dominant predictor ($\beta = 0.421$, $t = 7.938$, $p < 0.001$), confirming the rejection of H01. Social media sentiment retains a significant independent contribution ($\beta = 0.312$) even after controlling for VIX and news effects, confirming the rejection of H02. News sentiment contributes $\beta = 0.267$ to herding; when replicated with panic selling as the dependent variable, this coefficient rises to $\beta = 0.339$ ($p < 0.001$), confirming the rejection of H04. Consumer confidence is a significant negative predictor ($\beta = -0.198$, $p < 0.001$), confirming H03's rejection.

4.5 ANOVA Analysis

Respondents were classified into three equal-sized tertile groups based on composite sentiment score: Low Negative Sentiment (n = 70), Moderate (n = 70), and High Negative Sentiment (n = 70). The ANOVA result ($F(2, 207) = 38.742$, $p < 0.001$) is highly significant. Group means show a near-perfectly monotonic increase: Low (M = 2.81), Moderate (M = 3.52), High (M = 4.19) a 1.38-point spread on a 5-point scale. Post-hoc Tukey HSD tests confirm all three group pairs differ significantly (all $p < 0.05$). This dose-response pattern progressively higher herding as negative sentiment intensity increases converges with the regression findings and is consistent with both Prospect Theory and Information Cascade Theory.

4.6 Moderation Analysis and Qualitative Findings

The moderated regression interaction term (composite sentiment × investment experience) is significant ($\beta = 0.219$, $p = 0.012$), confirming the rejection of H05. More experienced investors demonstrate lower herding and panic selling under equivalent sentiment conditions compared with newer investors.

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Thematic analysis yielded four themes. First, fear as the dominant emotional register respondents across experience levels described real-time portfolio declines as overriding rational thinking even when their investment thesis had not changed. Second, social validation through digital communities younger investors reported consulting WhatsApp and Telegram channels before executing trades, providing qualitative corroboration for the social media regression coefficient. Third, information overload and decision paralysis investors with one to three years of experience described paralysis during conflicting sentiment signals, an inductive finding not anticipated in the hypothesis structure. Fourth, experience as a contextualising resource investors with more than five years consistently cited prior market cycles as a reference frame, suggesting that experience moderates sentiment effects primarily through cognitive reframing rather than superior information access.

V. FINDINGS AND DISCUSSION

Table 5: Summary of Hypothesis Testing Results

Hypothesis	Test Used	Key Statistic	Decision
H01: No VIX–herding relationship	Pearson r; Regression	$r = 0.614$; $\beta = 0.421$, $p < 0.001$	Reject H0
H02: Social media ≠ trading frequency	Pearson r; Regression	$r = 0.498$; $\beta = 0.312$, $p < 0.001$	Reject H0
H03: Consumer confidence ≠ risk appetite	Pearson r; Regression	$r = 0.441$; $\beta = 0.378$, $p < 0.001$	Reject H0
H04: News sentiment ≠ panic selling	Regression; ANOVA	$r = 0.603$; $F = 38.74$, $p < 0.001$	Reject H0
H05: Experience does not moderate	Moderated Regression	Interaction $\beta = 0.219$, $p = 0.012$	Reject H0

India VIX as a Behavioural Trigger. VIX perception is the strongest single predictor of herding ($\beta = 0.421$), establishing that perceived volatility anxiety functions not merely as a market-level barometer but as a near-behavioural trigger pushing retail investors toward crowd-following over independent analysis. Most existing VIX research focuses on aggregate pricing outcomes; this study extends that evidence base to the individual behavioural level.

Social Media as a Distinct Sentiment Channel. Social media sentiment retains a significant independent effect on herding ($\beta = 0.312$) and trading frequency ($r = 0.498$) after controlling for all other channels indicating it introduces distinct sentiment content rather than simply echoing existing market signals. This extends Bollen et al. (2011) to the Indian retail context using primary data.

News Tone and Panic Selling. Financial news sentiment shows the highest bivariate correlation with panic selling ($r = 0.603$). The way market stress is framed crisis language, alarming historical comparisons exerts a particularly strong pull toward panic responses, extending Tetlock's (2007) media pessimism findings to the Indian panic selling context.

Consumer Confidence as a Buffer. Consumer confidence is the only indicator with consistently negative relationships to adverse outcomes (herding: $r = -0.312$; panic selling: $r = -0.394$). This implies that macroeconomic communication by governments and central banks may have measurable downstream effects on retail investor behaviour during market stress events.

Experience Moderation. The interaction term $\beta = 0.219$ ($p = 0.012$) establishes that experience attenuates sentiment vulnerability. Unlike VIX levels or news tone, experience is developable through structured learning, paper trading, and deliberate post-mortem reviews of past sentiment-driven decisions making this the most actionable finding of the study.

VI. IMPLICATIONS

6.1 Theoretical Implications

The findings demonstrate that core behavioural finance mechanisms Prospect Theory loss aversion, noise trader dynamics, and information cascades are robust in the Indian retail investor context, which differs substantially in demographic profile and information environment from the Western settings where these constructs were originally developed. The multi-predictor regression also extends the Noise Trader Model by establishing that noise trader sentiment operates simultaneously through at least four distinct channels, each with partially different behavioural consequences. The social media result provides direct empirical support for a digital-age version of Information Cascade Theory that accounts for algorithmic amplification accelerating cascade formation.

6.2 Managerial and Regulatory Implications

For retail investors, the experience-moderation finding supports pre-committing to investment plans during calm periods through SIPs or written investment policy statements, providing mechanical discipline during high-sentiment events. For financial advisors, formally integrating India VIX monitoring into client communication protocols with pre-agreed escalation rules when VIX crosses defined thresholds could interrupt the sentiment-to-herding chain before decisions are executed. For brokerage platforms, embedding contextual sentiment indicators into trading interfaces could function as low-cost friction slowing impulsive decisions. For SEBI, the finding that news sentiment is the strongest predictor of panic selling provides empirical backing for regulatory scrutiny of financial media standards and social media influencer accountability, lending direct support to existing finfluencer disclosure guidelines.

VII. LIMITATIONS AND FUTURE RESEARCH

The cross-sectional design limits causal inference about the temporal sequence of sentiment changes and behavioural responses. Self-reported data on panic selling and overconfident trading carries social desirability risk; future research using objective brokerage transaction records would eliminate this concern. The non-probability sampling over-represents younger, digitally engaged urban investors, which may amplify social media sentiment effects relative to the broader national retail investor population. The study also does not distinguish between security types (large-cap vs. small-cap) or market phases (bull vs. bear).

Productive future directions include: longitudinal panel designs tracking the same investors across multiple market cycles; studies using objective brokerage transaction data matched to real-time sentiment indicators; sentiment analysis of vernacular Indian-language social media communities WhatsApp groups, regional YouTube channels, Telegram communities in Hindi, Tamil, and Telugu which remain almost entirely unstudied; and experimental designs using simulated trading environments to test precisely which sentiment features produce the largest behavioural effects.

VIII. CONCLUSION

The question motivating this study was whether market sentiment systematically shapes how retail investors in India actually behave. The data from 210 active investors provide a clear answer yes, considerably more so than many investors would probably acknowledge about themselves. Herding rises monotonically with negative market sentiment. Panic selling is most reliably triggered by financial news tone. Overconfident trading tracks positive social media sentiment. Consumer confidence pulls against these adverse tendencies. And across all four outcomes, investment experience consistently reduces sentiment vulnerability.

What matters most about these findings is that the effects are patterned and predictable not random failures, but structured responses to identifiable triggers. That makes them amenable to intervention through education, platform design, and regulatory action. The experience-moderation result carries particular optimism: the vulnerability to sentiment-driven errors diminishes with time and market exposure. How quickly that development can be accelerated, and through what institutional mechanisms, are questions with meaningful real-world stakes for the current generation of Indian retail investors.

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