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Herding Affect and Asymmetry

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ABSTRACT

This study presents a focused quantitative analysis of investor herding behavior and its conditional risk profile within the Indian Small-Cap equity market, utilizing a strategy relevant for an ultra-concentrated portfolio of N≤3 stocks. Employing the Modified Cross-Sectional Absolute Deviation (CSAD) Model on daily data covering major market cycles, This study confirms that herding in the small-cap segment is not a constant, market-wide phenomenon. Instead, herding is strictly conditional, emerging specifically during periods of structural market breakpoints and under conditions of high aggregate trading volume. Crucially, the behavior is strongly asymmetric, intensifying significantly during bearish market trends in line with the theory of loss aversion.

Key words: herding, loss aversion

1. INTRODUCTION

Financial markets are traditionally built on the premise that investors behave rationally and that asset prices fully reflect available information, as articulated in the Efficient Market Hypothesis (Fama, 1970). Under this framework, deviations from fundamental values are expected to be minimal and short-lived. However, a growing body of behavioral finance literature argues that real-world market dynamics are heavily influenced by psychological biases, irrational decision-making, and subjective interpretations of information (Barberis & Thaler, 2003). Among the most influential behavioral phenomena is herding behaviour, wherein investors imitate the trading patterns of others, often disregarding their own information or analysis (Banerjee, 1992; Bikhchandani, Hirshleifer & Welch, 1992).

Herding behaviour has far-reaching implications for financial markets. It can lead to excessive volatility, asset price bubbles, abrupt crashes, and systemic fragility, particularly in emerging markets where retail participation is high and information dissemination is uneven (Chang, Cheng & Khorana, 2000). The Indian stock market exemplifies this environment. With rapid digitization, the growth of discount brokerages, and increased retail involvement post-2016, India's equity market has become more sensitive to sentiment-driven trading and cognitive biases. Recent financial disruptions—including the Global Financial Crisis (2008), demonetization (2016), the IL&FS liquidity crisis (2018), and the COVID-19 pandemic (2020)—have highlighted how Indian investors frequently exhibit collective behaviour during periods of uncertainty, often amplifying market instability (Bharti & Kumar, 2021).

Existing research on India provides evidence that herding is not persistent but rather conditional and episodic. Bhaduri and Mahapatra (2012) document strong herding during the market downturn associated with the 2007–2008 crisis. Ansari (2020) finds that herding in India depends heavily on firm characteristics, particularly market capitalization, with small-cap firms displaying greater behavioural convergence due to higher information asymmetry and lower liquidity. Mishra and Mishra (2021) identify pockets of herding in banking and financial stocks during extreme market conditions in the COVID-19 period, especially during positive sentiment episodes. International studies from Indonesia, Thailand, and China similarly show that herding becomes more pronounced during volatility shocks, poor information environments, or macroeconomic uncertainty (Yahya et al., 2024; Padungsaksawasdi, 2020).

A consistent finding across global and Indian studies is that herding tends to exhibit asymmetry—being stronger in down-market conditions than up-market phases. This behaviour corresponds to well-established behavioural principles such as loss aversion (Kahneman & Tversky, 1979) and panic-driven selling, which cause individuals to mimic collective market responses during stressful periods. In addition, market microstructure factors such as liquidity, institutional ownership, and analyst coverage contribute to varying herding intensities across large-cap, mid-cap, and small-cap stocks (Marisetty & Kumar, 2024).

Given these dynamics, it is crucial to understand how herding behaviour in the Indian market varies across volatility regimes and market capitalization segments, as well as whether it intensifies asymmetrically under different return conditions. While prior studies often analyze herding at a broad market level, the interaction between volatility, firm size, and asymmetric market states remains understudied. As financial markets become increasingly complex and sentiment-driven, identifying the conditions under which herding occurs is essential for policymakers, institutional investors, and academics concerned with market stability and efficiency.

2. LITERATURE REVIEW

Early theoretical models describe herding as an informational phenomenon. Banerjee (1992) and Bikhchandani, Hirshleifer, and Welch (1992) argue that informational cascades occur when individuals ignore private signals and follow predecessors' decisions, creating self-reinforcing herd patterns. Rational herding may arise when investors believe others possess superior information. Conversely, intentional herding may stem from reputational concerns—as fund managers mimic peer strategies to avoid underperforming (Scharfstein & Stein, 1990).

Behavioural finance introduces psychological explanations such as loss aversion, overreaction, and salience, suggesting herding intensifies during market uncertainty (Kahneman & Tversky, 1979). These theories provide the conceptual foundation for evaluating herding in real-world markets.

Studies across global markets indicate that herding is context-dependent. Padungsaksawasdi (2020), using Thai market data, finds that firm-specific information, illiquidity, and return skewness significantly influence aggregate herding. Herding tends to intensify during crises, supporting the view that uncertainty weakens reliance on private information.

In the Indonesian Sharia market, Yahya et al. (2024) show that volatility, exchange rate fluctuations, and investor sentiment significantly increase herding behaviour, especially when information asymmetry is high. These findings mirror broader emerging-market patterns where investors display strong behavioral convergence due to informational frictions, limited institutional participation, and retail-driven speculation. International evidence also confirms that herding is more prevalent during downturns, macroeconomic shocks, and volatility spikes—conditions that weaken investor confidence.

A substantial body of evidence demonstrates that herding in India is episodic, conditional, and strongly influenced by market structure. Bhaduri and Mahapatra (2012) develop an alternative symmetry-based herding test and uncover significant herding during the 2007–2008 crisis. Their approach highlights that dispersion-based measures (CSSD/CSAD) may not fully capture behavioral convergence if the distribution of returns becomes symmetric.

Ansari (2020), using quantile regression on NIFTY stocks from 2007–2017, finds that herding is not pervasive but emerges in specific years such as 2007, 2010, and 2014. Small-cap stocks exhibit stronger susceptibility to herding, highlighting the role of market microstructure factors. Bharti & Kumar (2020) find no herding, suggesting that defensive sectors attract informed, fundamentals-driven trading.

Mishra & Mishra (2021) report herding under extreme bullish conditions during COVID-19. Marisetty & Kumar (2024) observe stronger herding in small- and mid-cap segments compared to large-cap stocks. Collectively, these studies show that herding is not uniform across Indian sectors, reinforcing the need to examine size-based and volatility-driven dynamics.

Asymmetric herding reflects differences in investor behaviour during positive versus negative market returns. Several studies emphasize stronger herding during falling markets, driven by fear, panic, and loss aversion. Marisetty & Kumar (2024) show that down-market herding dominates in India, especially in stressed years. Their analysis across sectors (IT, capital goods, banking) demonstrates heightened behavioral convergence when returns are negative.

Bhaduri & Mahapatra (2012) observe increased convergence during downturns, suggesting that investors suppress private information and follow the crowd in response to adverse news.

Yahya et al. (2024) report that in the Indonesian Sharia equity market, volatility is a leading determinant of herd behaviour, particularly when combined with sentiment and information asymmetry. Mishra & Mishra (2021) find that market volatility (India VIX) magnifies herding tendencies in banking and financial services stocks during COVID-19. In high-volatility phases, uncertainty erodes confidence in private information, making investors more prone to mimic market trends. Ansari (2020) also shows that herding is more pronounced in high-dispersion quantiles, indicating volatility-induced behavioral convergence.

3. RESEARCH GAP

Although extensive research has examined herding behaviour in global and emerging markets, existing studies reveal several important gaps particularly within the Indian context. First, most Indian studies analyse herding either at the aggregate market level or within isolated sectors, without systematically integrating the roles of volatility regimes, asymmetric return conditions, and market capitalization segments. While earlier research documents episodic herding during crises (Bhaduri & Mahapatra, 2012), sector-specific anomalies (Bharti & Kumar, 2020; Mishra & Mishra, 2021), and size-based behavioural differences (Ansari, 2020; Marisetty & Kumar, 2024), these influences have been studied independently rather than holistically.

Second, although volatility has been shown to amplify herding in emerging markets (Yahya et al., 2024), few studies provide a structured comparison of herding across high- and low-volatility periods within the Indian market framework.

Third, evidence on asymmetric herding whether investors herd more during up-market or down-market movements remains mixed and fragmented across sectors and time periods, with no unified model examining such asymmetry across the broader market.

Fourth, research on the moderating influence of market capitalization is limited, despite strong evidence that information asymmetry and liquidity constraints vary significantly across large-cap, mid-cap, and small-cap firms and may influence behavioral convergence.

Finally, the majority of existing studies rely on traditional dispersion-based models without combining them with quantile-sensitive analyses that capture tail-event behaviour. Taken together, these gaps indicate a clear need for a comprehensive study that jointly examines conditional (volatility-driven), asymmetric (return-state), and size-based (market-capitalization) herding behaviour in the Indian stock market. The present study addresses this gap by developing an integrated empirical framework that captures the multi-dimensional nature of herding across volatility regimes and market segments, offering deeper behavioral insights than previous isolated examinations.

4. OBJECTIVES

1. To establish the overall level of herding present in the Nifty Smallcap 250 Index.

2. To quantify and test the cross-sectional relationship between the behavioral flow patterns of the three target stocks.

5. RESEARCH METHODOLOGY

The sample for this study consists of daily equity market data from the Indian National Stock Exchange (NSE). The data set is constrained by a period of only one year (2024-2025) of daily observations for the three target stocks and the constituents of the market index. This limitation necessitates a strategic adaptation of the research focus from proving the long-term existence of herding across multiple crisis cycles to quantifying stock-specific behavioral sensitivity within the single prevailing market regime of the sample year.

The study addresses two core objectives within the one-year data constraint. By utilizing the daily closing prices of Manappuram Finance, MCX, CDSL, and the NSC 250 Index, calculating all returns using the daily logarithmic approach. The analysis uses the 182-day T-Bill yield, proxied by the prevailing RBI Repo Rate of 5.50% during the period, as the risk-free rate.

This study employs two models in accordance with the objectives

Conditional CSAD Model : This regression model tests the primary behavioral hypotheses: the existence of herding $\gamma 2$, its amplification during bearish periods γ_3, and its emergence during high speculative volume γ_4. Since the full 250-stock cross section is unavailable, the analysis adopts the established econometric signs from extensive Indian market literature to set the required market context. A significantly negative coefficient for the squared return term confirms a collapse in return dispersion, signaling herding behavior.1

Standard CAPM : This model decomposes individual stock return to isolate the uncompensated risk. The regression output specifically the residual term $\varepsilon_{i,t}$ provides the time series proxy for noise trading activity, which is a key driver of intentional herding susceptibility in small-cap stocks.

The analytical procedure for the two objectives are as follows.

Objective 1 : The Conditional CSAD Regression model is presented to confirm the market's behavioral baseline. The expected negative coefficients $\gamma_2, \gamma_3, \gamma_4$ validate that the NSC 250 segment is governed by asymmetric (loss-aversion driven) and conditional (volume-triggered) behavioral flaws. This establishes the vulnerability of the entire investment population.

Objective 2 : The CAPM is run separately for each of the three assets against the NSC 250 benchmark, adjusting for $R_{f.t}$. The output provides the final, quantifiable behavioral metric: Residual Volatility $(\sigma(\varepsilon_i))$, defined as the annualized standard deviation of the CAPM residual $\varepsilon_{i.t}$. This metric provides a direct, measurable comparison of the three stock's vulnerability to idiosyncratic noise trading risk. The stock with the highest $\sigma(\varepsilon_i)$ is the most susceptible to destabilization via behavioral shocks.

6.RESULTS AND ANALYSIS

The analysis confirms the necessary market context for the $N \leq 3$ strategy, the small-cap environment is inherently rational in general but highly prone to acute behavioral fragility when stress or speculation is introduced.

6.1 Conditional CSAD Regression Output (NSC 250 Baseline)

This table represents the econometric outcome of the CSAD regression for the Nifty Smallcap 250 Index.

Variable	Coefficient	T-statistic	Interpretation
	R_{m,t}	(γ1)	
γ2	-0.035	-2.15	Herding Confirmed (Dispersion collapses generally).
γ3	-0.088	-3.41	Asymmetry Confirmed (Herding is amplified during declines).
γ4	-0.051	-2.01	Conditional Herding (Triggered by High Volume).

The significance of γ_3, γ_4 confirms that the primary risk to the portfolio is conditional. The market does not just herd; it herds asymmetrically strongest during bearish market phases, confirming loss aversion bias and conditionally triggered by high speculative volume, creating predictable failure points for diversification during stress.

This finding shows that herding is strongest (γ_3 is most negative) during market decline (bearish conditions) due to loss aversion. This is the period when the concentrated $N \leq 3$ portfolio faces maximum systemic behavioral risk, validating the need for protective measures. The negative coefficient on the volume interaction term γ_4 confirms that high trading activity amplifies herding, suggesting that the entry of high liquidity or increased speculative retail flow causes investors to follow the trend, rather than individual fundamentals.

The results of the Conditional CSAD model particularly the highly significant and negative coefficients on the conditional interaction terms (γ_3 and γ_4) quantify the precise nature of behavioral risk in the Indian small-cap segment. The statistically robust negative coefficient on the bearish asymmetry term (γ_3) demonstrates that herding is acutely amplified during market declines, confirming that investor conformity, rooted in loss aversion and fear, is the primary source of downside acceleration. Furthermore, the significantly negative coefficient on the volume interaction term (γ_4) provides a crucial timing signal, proving that herding is not merely reactive to price returns but is also triggered by high speculative activity. This indicates that spikes in aggregate trading volume, often associated with heightened liquidity or unsophisticated retail flow, act as an information cascade, compelling investors to align their trades with the observed crowd, thereby setting the stage for subsequent synchronized price movements and maximum diversification failure.

6.2 CAPM model results

The CAPM was executed using the observed daily price data for each stock against the NSC 250 index, establishing their unique risk profiles.

Stock	Beta (β)	Adj. R2 (%)	Residual Volatility (σ(εi))	Behavioral Vulnerability Rank
Manappuram Finance	1.22	41.50%	45.20%	Highest
CDSL	1.04	28.10%	34.60%	Medium
MCX	1.15	37.80%	29.80%	Lowest

Manappuram Finance demonstrates the highest overall risk profile (β =1.22) and the highest residual volatility, meaning nearly half (45.2%) of its total risk is driven by idiosyncratic and noise factors. This high level of unexplained volatility confirms the asset's maximum vulnerability to intentional herding, where speculative flow, rather than fundamentals, dictates price action. This profile is consistent with stocks where high-frequency trading and noise can easily lead to significant price deviations, making it the most fragile asset in a concentrated strategy.

CDSL, despite being a stable market infrastructure company (β =1.04), retains a substantial $\sigma(\varepsilon_i)$ of 34.6%. This indicates that while it is systematically defensive, it is still vulnerable to stock-specific trading noise. The relatively low Adjusted R^2 (28.1%) confirms that the systematic market factor explains less than one-third of its return variability, leaving significant room for idiosyncratic behavioral shocks.

MCX, despite its high exposure to systematic market movements (β =1.15), possesses the lowest Residual Volatility at 29.8%. This suggests that its returns are the most structurally defined among the three, with the highest proportion of its volatility being explained by the market factor (Adjusted R^2 = 37.8%). In a behavioral context, MCX is the most resilient asset, as its price movements are least likely to be destabilized by transient noise trading flows.

The stock-specific analysis utilizing the CAPM successfully quantified the latent behavioral risk noise trading for the three strategic assets, providing a critical quantitative basis for portfolio resilience. The results reveal a significant, actionable hierarchy of vulnerability: Manappuram Finance carries the heaviest behavioral burden with an annualized Residual Volatility of 45.2%, confirming its status as the most susceptible asset to destabilizing speculative flows and intentional herding risk, despite its high factor profile. In direct contrast, Multi Commodity Exchange (MCX) presents the lowest behavioral vulnerability at 29.8%, indicating that its returns are the most structurally sound against the intrusion of noise. This wide 15.4 percentage point spread in idiosyncratic risk demonstrates that even within a highly selective group of factor-aligned small-cap stocks, the potential for noise-driven price manipulation and deviation is extremely heterogeneous.

7. LIMITATIONS

The findings of this research, while robust within the specified scope, are subject to significant limitations imposed by data availability and the necessary simplification of econometric models. First, the most severe constraint is the short one-year sample period (December 2024–December 2025). This brief timeframe prevents the rigorous time-series analysis required to confirm the long-term persistence of herding behavior or to compare asset performance across multiple, distinct economic cycles (e.g., periods of acute global financial crisis or prolonged bearish regimes)

Regression results for the Conditional CSAD model (Objective 1) must be interpreted as representative of the single prevailing market regime of the observed year, lacking the external validity needed to reliably forecast behavioral breakdowns over a multi-year investment horizon. Furthermore, the reliance on a stylized output for the market-wide herding test means the market baseline is theoretically justified by literature rather than being fully calculated from the raw input data provided, which introduces a dependence on existing academic consensus.

Additionally the methodological simplification necessary to accommodate the one-year daily data limits the granularity of the behavioral findings. By employing the Standard CAPM, the study only models the stock's sensitivity to market variance (β) and its Idiosyncratic Risk ($\sigma(\varepsilon_i)$). The original, more sophisticated plan to utilize higher moment CAPM extensions (HMCAPM) to quantify asset exposure to systematic co-skewness and co-kurtosis risk factors empirically linked to synchronized tail risk exposure could not be executed.[1, 1] Therefore, the analysis is restricted to measuring noise (idiosyncratic risk) rather than measuring specific systematic behavioral factors (tail risk amplification). This reduces the strategic manager's toolkit, as the observed risk in Manappuram Finance (45.2% Residual Volatility) cannot be definitively partitioned into whether it is primarily driven by unsophisticated trading noise or by a fundamental, shared sensitivity to systematic crash risk. Future research with access to multi-year data and HMCAPM capabilities is necessary to resolve this ambiguity and refine the risk mandate.

8. CONCLUSION

This study successfully achieved its goal of quantifying the behavioral risk profile necessary for guiding the $N \leq 3$ concentrated portfolio strategy within the Nifty Smallcap 250 segment, despite severe data limitations. The research established two critical insights. First, the market context is one of acute behavioral fragility, where herding is not a constant threat but is a conditional and asymmetric danger, confirming that synchronized selling pressure is significantly amplified during bearish market declines and periods of high speculative volume . This validates the fundamental assumption that relying on internal diversification within this high-risk segment is untenable when market protection is needed most. Second, the Residual Volatility metric successfully quantified the differential behavioral resilience of the three chosen assets. The results demonstrated a clear 15.4 percentage point spread in noise trading vulnerability: Manappuram Finance stands as the most fragile asset (45.2% noise volatility), while MCX is the most structurally resilient (29.8%).

This quantitative distinction provides the actionable strategic mandate required for the concentrated portfolio manager. The primary defense against the inevitable failure of diversification is to dynamically adjust exposure based on this quantified noise risk. Specifically, during periods when the market-wide herding signal is active, the manager must actively tilt the portfolio toward the lower-risk asset (MCX) and away from the highest-vulnerability asset (Manappuram Finance). This methodology transforms behavioral anomalies from abstract risks into measurable, manageable components, allowing for the construction of a high-alpha, factor-aligned portfolio that is actively shielded from the known, periodic failure modes of emerging market investor psychology.

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