



Herding Behaviour in the Indian Equity Market: Evidence from the NSE Chemical Sector

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Abstract: This study examines herding behaviour among NSE-listed chemical sector companies by using daily closing prices from 1 April 2015 to 31 March 2025. It is based on three models i.e., the traditional CSAD model, the extended Chiang and Zheng model, and a modified CSAD approach. Quantile regression is used to capture how investor behaviour changes across different market states. Further, a rolling-window extension tracks how it varies over time. The result shows the herding in the chemical sector occurs mainly at the lower quantiles of overall, bearish and extreme bearish market periods. However, the return dispersion increases during bullish, extreme bullish or normal phases. The rolling-window estimates show that this behaviour is mainly concentrates in the COVID-19 crisis and the 2022 commodity shock. It is largely absent during the 2016-2018 Supercycle and the post-2023 stabilisation. This study adds value in the field of behavioural finance. Herding in the chemical sector is episodic, asymmetric, and conditioned by the macroeconomic environment rather than continuously present. The study can be further extended by incorporating intraday data, market sentiment and the difference between institutional and retail investors.

Keywords: Herding, CSAD, quantile regression, behavioural finance, chemical sector.

1. Introduction

Financial markets in developing economies have changed rapidly over the last few decades. Advances in trading technology, broader participation by retail and institutional investors, and deeper integration with global markets have reshaped the price formation process. As a result, a wide range of market anomalies has become more visible. Behavioural anomalies arise when investor behaviour deviates from the assumptions of traditional finance (Fama, 1970; Shrotryia & Kalra, 2019). Herding, among these anomalies, is one of the most widely examined and refers to the inclination of investors to follow the market ignoring their private information. Herding has significant implications for informational efficiency, prices, and volatility. Therefore, understanding herding is pivotal to any evaluation of market stability.

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Many sectors, namely, manufacturing, pharmaceuticals, textiles, , and agriculture procure inputs from the chemical sector, which has exposure to external forces that are beyond its control: international demand, global commodity prices, trade policy, environmental regulation, and changes in domestic demand. As the chemical sector is sensitive to aforesaid external forces, predicting investor behaviour in this sector is difficult and thus this sector makes a good case for studying how investor behaviours respond to varying market dynamics.

In prior studies, herding has been examined overall instead of examining it across levels of market stress, volatility and abnormal return movements. As the market behaviour can vary significantly across bullish, bearish, calm, normal, highly volatile phases, a more granular analysis is the need of hour. Herding in the chemical sector in both overall and asymmetric market conditions from 2015 to 2025 has been examined in this study. Using a rolling-window specification, the study extends the analysis in time and thus it contributes to the extant literature of behavioural finance pertaining to a sector having reasonable macroeconomic significance. Also, the study offers evidence relevant to policymakers, regulators, and institutional investors functioning in India's dynamic financial system.

2. Literature Review

Investors' herding behaviours are often contemplated as a source of instability in the market. According to Christie and Huang (1995, p. 31), it is one of the important factors driving volatility, while Chari and Kehoe (2004) report that financial stress can deepen to the point of triggering crises when large groups of investors behave in the same way. The presence of herding in financial markets is a well-established fact (Devenow & Welch, 1996).

People follow the actions of others even when their own information points elsewhere (Banerjee, 1992). In market literature, herding is generally described as coordinated trading caused by investors observing and reacting to one another (Chiang

& Zheng, 2010, p. 1911). In the present study, the definition given by Hwang and Salmon (2004, p. 585) is adopted. According to this definition, herding occurs when market trends or the decisions of other investors are followed instead of independent analysis and private information.

Herding can be classified as intentional or spurious. Intentional herding is observed when other investors are deliberately followed, which may lead to inefficient price movements. Spurious herding is observed when similar decisions are made because the same information is being received. These two forms are difficult to separate in empirical studies although they are conceptually different, because the observed behaviour is impacted by psychological factors, information conditions, , and institutional settings (Bikhchandani & Sharma, 2000).

Herding can also term as rational or non-rational (Devenow & Welch, 1996). Rational herding is caused by information gaps, concerns about reputation or the desire to avoid performing worse than others. Non-rational herding is driven by fear, overreaction, uncertainty, and the tendency to imitate others.

In this study, herding is examined as a situation in which firm-specific fundamentals are ignored and broader market movements are followed by investors (Henker et al., 2006). This distinction is important because asset prices may be pushed away from their intrinsic values. As a result, portfolio decisions may be distorted (Tan et al., 2008), the independence of stock-price movements may be reduced and market efficiency may be weakened (Chiang & Zheng, 2010, p. 1911).

Several theoretical explanations have been proposed for herding. It was shown by Scharfstein and Stein (1990) that fund managers may be influenced by reputational concerns. As a result, the decisions of other managers may be followed, while superior private information may be ignored. This argument was extended by Welch (1992) to sequential investment decisions. It was demonstrated that private signals may be suppressed by well-informed analysts so that market consensus can be followed, thereby causing information cascades. It was found by Avery and Zemsky (1998) that herding may be strengthened by different forms of uncertainty, particularly when fundamental price movements cannot be distinguished from sentiment-driven

movements. It was also shown by Froot, Scharfstein, and Stein (1992) that herding may be rationally adopted by short-term investors because similar profits may be generated by trading on common short-term signals. However, long-term price efficiency may be weakened by such behaviour.

The empirical measurement of herding was first developed by Christie and Huang (1995) through the Cross-Sectional Standard Deviation (CSSD) framework. Under this approach, stock returns are expected to move closer to the market return during large market movements when investors' own beliefs are ignored and market consensus is followed. The method was later improved by Chang, Cheng, and Khorana (2000) through the introduction of the Cross-Sectional Absolute Deviation (CSAD) measure. CSAD is less affected by extreme values and is more suitable for identifying non-linear patterns in return dispersion. It has since been widely used in herding research. The model was further extended by Chiang and Zheng (2010) to test herding separately under bullish and bearish market conditions across eighteen global markets. Widespread herding was identified, particularly in Asian markets.

The empirical measurement of herding has been developed considerably since the Cross-Sectional Standard Deviation (CSSD) framework was introduced by Christie and Huang (1995). Under this framework, individual stock returns are expected to move closer to the market return during large market movements when investors' own beliefs are ignored and market consensus is followed. The approach was later refined by Chang, Cheng, and Khorana (2000) through the Cross-Sectional Absolute Deviation (CSAD) measure. CSAD is more suitable for detecting non-linear patterns in return dispersion. It has since been widely used in the herding literature. The model was further extended by Chiang and Zheng (2010) to examine herding separately during bullish and bearish market conditions across eighteen global markets. Widespread herding was found, particularly in Asian markets.

Mixed findings have been reported across different markets. Herding under adverse market conditions was identified in the Italian equity market by Caparelli, D'Arcangelis, and Cassuto (2004). In contrast, limited evidence of herding was found in Chinese equity markets by Demirer and Kutan (2006). This suggests that herding may be influenced by specific sectors and market conditions rather than being present

in all markets. Early evidence from US pension fund portfolios was provided by Lakonishok, Shleifer, and Vishny (1992), who found that similar trading directions were followed by money managers over successive periods. Evidence from emerging markets was reviewed by Bikhchandani and Sharma (2000), and stronger herding was found in markets where informational efficiency was lower and investors were less sophisticated. Economou, Kostakis, and Philippas (2011) applied quantile regression to Southern European markets and found herding to be stronger at the extreme tails of the return distribution. This finding corroborates the application of quantile approach in this study.

In the Indian markets, the evidence on herding is limited. Shrotryia and Kalra (2019) examined herding in the Indian stock market and found clustering of stock returns during high volatility regimes. Therefore, it is important to examine herding under different market dynamics. Garg and Gulati (2013) studied the Indian derivatives market and reported stronger herding during high-volatility periods. The theoretical arguments developed by Avery and Zemsky (1998) is consistent with this result. Bekiros, Jlassi, Lucey, Naoui, and Uddin (2017) studied herding at the sectoral levels and showed that herding in cyclical and commodity-related industries may vary significantly from overall market movements. Their study supports the need for sector-specific analysis.

The Indian chemical sector has not been studied exclusively in spite of the growing literature. Consequently, investor behaviour in the Indian chemical sector remains insufficiently understood even though the sector is significantly influenced by regulatory changes, global commodity prices, and export-driven demand. This study makes an attempt to fill this gap.

3. DATA AND METHODOLOGY

3.1 Data and Sample Construction

Covering a sample period from 1 April 2015 to 31 March 2025, Herding behaviour among chemical sector companies listed on the NSE has been studied under different market dynamics. The study uses a sample of seventeen chemical companies (refer Annexure I) from the Nifty Chemicals Index. Three companies were excluded out of the twenty companies, because of insufficient price data availability for the sample period. Also, Firms companies that were got acquired, delisted, acquired, or removed from the index during the study sample period are not included in excluded from the sample.

The rationale for the ten-year sample period is twofold. First, 31st March 2025 provides a consistent time frame as it coincides with the end of the Indian financial. Second, the sample period covers several different market phases including the chemical sector flourishing from 2015 to 2018, the market fall during 2018–2019, the COVID-19 crisis and the V-shaped recovery during 2020–2021, the commodity price trouble owing to the Russia–Ukraine conflict in 2022, and the market regularisation period from 2023 to 2025. Thus, the sample period allows us to examine herding under different market conditions, which is of paramount importance for the rolling-window analysis shown in Section 4.5.

3.2 Variable Construction

Stock Returns ($R_{k,t}$): Daily stock return equals the natural logarithm of the ratio of the closing price on day t to the closing price on day $t-1$.

Market Return ($R_{m,t}$): the market return is calculated as the equally weighted average of the daily returns of all sample constituent companies for each trading day.

Cross-Sectional Absolute Deviation (CSAD): CSAD measures the dispersion of individual stock returns from the market mean and indicates the extent of convergence or divergence of stock-specific returns diverge from the overall market return for a particular day.

$$CSAD_t = (1/N) \sum_{k=1}^N |R_{k,t} - R_{m,t}|$$

Where,

N = Total number of individual stocks considered in the calculation of the dispersion measure.

3.3 Herding Under Overall Market Conditions

The baseline model of Chang et al. (2000) is estimated, as shown in Equation (1), to assess herding in the overall market.

$$CSAD_t = \alpha + \gamma_1 |R_{m,t}| + \gamma_2 R_{m,t}^2 + u_t \quad (1)$$

Where,

γ_1 = linear effect of market movement on return dispersion

α = constant

u_t = error term.

The evidence of herding is found, when γ_2 is negative and statistically significant, which implies that investors are blindly following the aggregate market trend instead of acting on their analyses.

3.4 Herding in Bullish and Bearish Market Conditions

The approach of Chiang and Zheng (2010) is applied to detect herding separately under bearish and bullish conditions.

$$CSAD_t = \alpha + \gamma_1 DBU |R_{m,t}| + \gamma_2 DBU (R_{m,t})^2 + \gamma_3 DB |R_{m,t}| + \gamma_4 DB (R_{m,t})^2 + u_t \quad (2)$$

At time t , $DB = 1$ when the market return is negative ($R_{m,t} < 0$), signalling a bearish phase, and 0 otherwise. Similarly, $DBU = 1$ when $R_{m,t} \geq 0$, indicating a bullish period. Herding is present when the non-linear coefficients γ_2 for bullish markets and γ_4 for bearish markets are negative and statistically significant.

3.5 Herding During Extreme and Normal Market Conditions

The following modified framework is estimated to capture herding during normal, extreme bullish, and extreme bearish periods.

$$CSAD_t = \alpha + \gamma_1 D_XBEAR |R_{m,t}| + \gamma_2 D_XBEAR R_{m,t}^2 + \gamma_3 D_NORM |R_{m,t}| + \gamma_4 D_NORM R_{m,t}^2 + \gamma_5 D_XBULL |R_{m,t}| + \gamma_6 D_XBULL R_{m,t}^2 + u_t \quad (3)$$

Here $D_XBEAR = 1$ when the market return $R_{m,t}$ falls at or below the lower cut-off, the 5th percentile of the market return distribution, indicating an extreme bearish regime, and 0 otherwise. $D_XBULL = 1$ when $R_{m,t}$ is at or above the upper cut-off, the 95th percentile, indicating an extreme bullish regime. The normal-market dummy D_NORM equals 1 when the market return lies between the 5th and 95th percentiles, representing non-extreme conditions. Both thresholds are obtained from the empirical distribution of the overall market return series.

Herding is present when the non-linear coefficients are negative and statistically significant: γ_2 during extreme bearish periods, γ_4 under normal conditions, and γ_6 during extreme bullish phases.

3.6 Estimation Method

Quantile regression (Koenker & Bassett, 1978) is used to estimate all three specifications at the 10th, 25th, 50th, 75th, and 90th quantiles. In conventional OLS-based herding studies, average effects are estimated and regime-specific dynamics may therefore be masked. By conditioning on the full distribution of return dispersion, quantile regression can be used to detect herding that is present only at lower quantiles or only during high-volatility episodes at upper quantiles. This approach was adopted following Economou et al. (2011) and in response to calls for distributional methods in herding research made by Tan et al. (2008).

3.7 Time-Varying Herding: A Rolling-Window Quantile Regression

Conventional quantile regression is static: it pools the entire sample and cannot reveal whether herding is stable across time. To address this, the baseline model (Equation 1) is re-estimated at Q10 and Q50 over a rolling window of 250 trading days, approximately one calendar year, generating a time series of γ_2 estimates across the sample period. The Q50 serves as a central benchmark relative to conventional OLS estimates while the Q10 captures the regime in which the static analysis identifies herding most consistently. The approach preserves parsimony and follows established practice (Economou et al., 2011).

The full sample is pooled in conventional quantile regression. As a result, changes in herding over time cannot be traced. The baseline model in Equation (1) is re-estimated at Q10 and Q50 using a rolling window of 250 trading days to address this limitation. Thereafter, a time series of γ_2 estimates is obtained for the full sample period.

This specification furnishes a valid test. The γ_2 estimates are expected to remain relatively stable over time when herding is a structural feature of the sector. If herding, however, is episodic and is impacted by changes in market sentiment and macroeconomic conditions, noticeable variation is likely to be seen in the rolling estimates for specific sub-periods.

4. Findings and Discussions

4.1 Descriptive Statistics

Table 1 presents descriptive statistics and the outputs of the Jarque–Bera and ADF tests for each market phase. Also, it reports the changes in stationarity, dispersion, and distribution across different market dynamics.

Under normal market conditions, the mean CSAD appears to be stable at around 0.0124. However, it is increased to 0.0180 during extreme bullish periods and 0.0172 during extreme bearish periods. This shows that return dispersion becomes wider when strong market movements are experienced in either direction. For the full sample, CSAD is found to range from 0.0037 to 0.0369, with the highest value being recorded during a bearish trading day. Market returns are found to remain close to zero in the overall and normal samples. Positive returns are observed during bullish and extreme bullish periods, while negative returns are observed during bearish and extreme bearish periods. The returns range from -0.1299 to 0.0608 .

Positive skewness is observed in CSAD across all market conditions. Positive skewness is also found in market returns during bullish periods, while negative skewness is observed during bearish periods. This shows that upward movements are more common in bullish markets, whereas sharper declines are more common in bearish markets. Leptokurtosis is found in both series. CSAD kurtosis ranges from 3.76 during extreme bullish periods to more than 6 during bearish periods. Return kurtosis

reaches nearly 27 under bearish conditions. This indicates the presence of extreme market movements and volatility clustering in the chemical sector.

Normality is rejected at the 1% level by the Jarque-Bera test across all market conditions. Stationarity of both CSAD and market returns is confirmed by the ADF test. Therefore, no unit root is found in either series and both series are considered suitable for further econometric analysis.

TABLE 1: SUMMARY OF DESCRIPTIVE STATISTICS

Variable	Obs	Mean	Std. Dev.	Min	Max	Skewness	Kurtosis	Jarque-Bera	ADF
CSAD	2,475	0.012896	0.004513	0.003741	0.036899	1.186975	5.409971	1180*	-29.1*
Rm	2,475	0.000902	0.012584	-0.12986	0.060844	-1.089289	11.059740	7188*	-34.6*
CSAD (Bullish)	1,403	0.013263	0.004531	0.003741	0.036331	1.110280	4.914120	502.40*	-28.8*
Rm (Bullish)	1,403	0.008802	0.007319	0.000004	0.060844	1.826420	8.633830	2636*	-32.1*
CSAD (Bearish)	1,072	0.012417	0.004445	0.004070	0.036899	1.317800	6.269800	787.90*	-22.3*
Rm (Bearish)	1,072	-0.009437	0.010341	-0.12986	-0.00004	-3.470440	26.997200	28000*	-26.9*
CSAD (Extreme Bullish)	124	0.017955	0.005410	0.008887	0.036331	0.782850	3.759000	15.64*	-10.5*
Rm (Extreme Bullish)	124	0.025618	0.007820	0.018724	0.060844	1.886280	6.720140	145*	-2.6**
CSAD (Extreme Bearish)	124	0.017238	0.005557	0.008779	0.036899	1.276530	4.913450	52.59*	-8.46*
Rm (Extreme Bearish)	124	-0.030852	0.014599	-0.12986	-0.01982	-3.526000	20.777800	1890*	-13.9*
CSAD (Normal)	2,227	0.012373	0.004069	0.003741	0.034147	1.038000	4.863800	722.3*	-42.9*
Rm (Normal)	2,227	0.001294	0.008396	-0.01967	0.018677	-0.214606	2.515170	38.91*	-7.77*

Source: Author's calculations.

Notes: *t*-values are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

4.2 Herding Under Overall Market Conditions

Quantile regression estimates for the overall market are presented in Table 2. The coefficient of the squared market return term, γ_2 , is found to be negative and statistically significant at Q10 and Q25. This shows that similar investment behaviour is followed

when return dispersion is low and price movements are relatively small. Individual assessments may be set aside, and the general market trend may be followed instead. This result is in line with Bikhchandani and Sharma (2000) and Chiang and Zheng (2010), who show that lower return dispersion and herding may be seen when investors follow the market consensus.

No systematic herding is traced under normal or moderately active market dynamics as the coefficient is statistically insignificant at Q50 and Q75. In such scenarios, investment decisions are made primarily based on company-specific information ignoring the overall market sentiment.

The squared market return coefficient is negative and significant at the 10% level At Q90 indicating that slight herding may be detected during highly instable market conditions. The broader market direction may be imitated by some investors under reputational pressure and greater information uncertainty. This is consistent with the mechanism explained by Scharfstein and Stein (1990). However, the result should be interpreted cautiously because of its weak statistical significance.

Overall, herding is observed during highly stable and highly uncertain market conditions, while independent investment decisions are made under normal conditions. This pattern is consistent with Demirer and Kutan (2006), where herding in emerging markets is found to be episodic and dependent on market conditions rather than continuous.

TABLE 2: OVERALL MARKET CONDITIONS IN CHEMICAL SECTOR

CSAD _t	Quantile 10 (Q10)	Quantile 25 (Q25)	Quantile 50 (Q50)	Quantile 75 (Q75)	Quantile 90 (Q90)
$ R_{mst} $	0.188* (11.34)	0.237* (13.62)	0.248* (13.71)	0.273* (11.50)	0.344* (9.01)
$(R_{mst})^2$	-0.670** (-2.28)	-1.125* (-3.66)	-0.310 (-0.97)	-0.067 (-0.16)	-1.230*** (-1.80)
Constant	0.007* (46.54)	0.008* (53.40)	0.010* (64.36)	0.013* (60.49)	0.015* (45.60)

*Source: Author's calculation. Notes: t-values in parentheses. *, **, and *** indicate statistical significance at the 1%, 5%, and 10% levels respectively.*

4.3 Herding Under Bearish and Bullish Market Conditions

Herding is not observed uniformly across bullish conditions (Table 3). During the bullish phase, the non-linear coefficient is found to be negative and statistically significant only at Q10. At Q25 and the higher quantiles, statistical significance is not found. This is evidence for the fact that similar investment decisions are taken when the market upsurges moderately and volatility tends to be low. Decisions are likely to be taken based more on company-specific information under other bullish conditions.

The bearish phase experiences a different pattern. The squared coefficient is negative but statistically insignificant at Q10 and Q25 furnishing no evidence of herding at these quantiles. The coefficient is positive and statistically significant at Q50, Q75, and Q90, indicating that investors do not follow the general market trend when the market declines. Consequently, more independent investment behaviour and wider return dispersion are likely to be observed. This insight is in line with Tan et al. (2008) who show evidence of anti-herding among Chinese equity investors during bearish periods and argue that importance should be given to company-specific information when the market plunges abruptly.

TABLE 3: BEARISH AND BULLISH MARKET CONDITIONS IN CHEMICAL SECTOR

Phase	Variables	Q10 [Calm]	Q25 [Mod. Low]	Q50 [Normal]	Q75 [Mod. High]	Q90 [High Vol.]
Bullish	DBU $ R_{mst} $	0.280* (8.98)	0.247* (8.73)	0.287* (10.14)	0.290* (7.19)	0.412* (6.60)
	DBU $(R_{mst})^2$	-2.900* (-2.80)	0.769 (0.83)	0.135 (0.15)	0.893 (0.68)	-2.161 (-1.10)
Bearish	DB $ R_{mst} $	0.170* (7.78)	0.159* (8.26)	0.165* (8.56)	0.180* (6.55)	0.165* (3.90)
	DB $(R_{mst})^2$	-0.490 (-1.40)	-0.128 (-0.40)	0.720** (2.31)	0.994** (2.23)	3.189* (4.60)
	Constant	0.010* (38.10)	0.008* (52.80)	0.010* (65.23)	0.013* (56.91)	0.015* (44.40)

Source: Author's calculation. Notes: as Table 2.

4.4 Herding During Extreme and Normal Market Conditions

Table 4 presents investor behaviour in normal, extreme bearish, and extreme bullish periods. During extreme bearish regimes, the squared return coefficient is found to be negative and significant at Q25 and Q50, and negative at Q10 even though significant only at the 10% level. Driven by fear and uncertainty rather than fundamentals, investors tend to act similarly in sharply declining markets. This convergence appears to be in line with cascade-driven behaviour, in which fear and information uncertainty make investors imitate the crowd abandoning private signals (Banerjee, 1992). The squared term is positive and significant at most quantiles under normal conditions, showing dispersion instead of convergence and thus shows an evidence of anti-herding. The squared coefficient is found to be neither negative nor significant at any quantile in extreme bullish markets, implying dispersion instead of convergence.

The absence of herding during these phases may be explained by the fact that positive sentiment in the chemical sector is generally supported by identifiable fundamental factors, such as export cycles and commodity price trends. Consequently, differentiated information can be used in investment decision-making.

Overall, herding is observed only during periods of downward market pressure. During normal and extreme bullish phases, investment decisions are made on the basis of individual assessments, showing that trading in the sector is largely driven by information.

TABLE 4: QUANTILE REGRESSION RESULTS IN EXTREME AND NORMAL MARKET CONDITIONS

Market Phase	Variables	Q10 [Calm]	Q25 [Mod. Low]	Q50 [Normal]	Q75 [Mod. High]	Q90 [High Vol.]
Extreme Bearish	D_XBEAR	0.170* (7.35)	0.200* (8.62)	0.230* (9.62)	0.170 (5.10)	0.240* (4.52)
	$R_{m,t}^2$	-0.600* (-1.63)	-0.860** (-2.49)	-1.230* (-3.40)	1.030 (2.06)	0.650 (0.82)
Normal	D_NORM	0.030 (0.47)	-0.010 (-0.16)	-0.020 (-0.27)	-0.030 (-0.35)	0.110 (0.74)
	$R_{m,t}^2$	7.990** (2.11)	11.770* (3.20)	15.180* (3.91)	18.280 (3.41)	13.140 (1.55)
Extreme Bullish	D_XBULL	0.160* (3.47)	0.180* (3.96)	0.260* (5.40)	0.310 (4.68)	0.400* (3.80)

	D_XBULL $R_{m,t}^2$	-0.260 (-0.19)	1.930 (1.47)	0.100 (0.07)	-1.410 (-0.74)	-2.310 (-0.80)
	Constant	0.010* (31.10)	0.010* (39.40)	0.010* (45.60)	0.010 (40.6)	0.020* (30.50)

Source: Author's calculation. Notes: as Table 2.

4.5 Time-Varying Herding: Rolling-Window Results

In Tables 2 to 4, herding is mainly identified at the lower quantiles of the conditional dispersion distribution. However, these estimates are obtained from the full sample and do not show how herding changes over time. Therefore, it is examined whether low-dispersion days are spread evenly across the study period or are concentrated in specific market phases. This issue is examined in Table 5 and Figure 1 through 250-day rolling estimates of γ_2 at Q10 and Q50.

It is found that low-dispersion days are concentrated in specific periods. During the chemical sector boom and the subsequent correction, positive γ_2 estimates are mainly observed at both quantiles, while negative estimates account for less than 11% of the rolling windows. Therefore, no clear evidence of herding is found during these phases. Investment decisions appear to have been based mainly on fundamental and stock-specific information, which is consistent with the findings of Demirer and Kutan (2006) for information-rich periods.

The strongest evidence of herding is observed during the COVID-19 crisis. The mean γ_2 is reduced to -0.53 at Q10 and -1.35 at Q50. Negative estimates are found in 76.2% of the rolling windows at Q10 and 81.0% at Q50. This indicates that similar trading behaviour was followed because of fear, uncertainty, and panic selling. This finding is consistent with Banerjee (1992), where private information is expected to be ignored and the behaviour of others is followed during extreme conditions.

Herding at Q50 is also observed during the recovery period, with negative estimates in 87.8% of the rolling windows and a mean γ_2 of -0.84 . Stronger herding is found during the geopolitical shock of 2022, when negative estimates are observed in 89.5% of the windows and the mean γ_2 falls to -2.23 . During this period, the chemical sector was directly affected by disruptions in fertiliser and petrochemical supply chains caused by the Russia–Ukraine conflict. At Q10, a mixed result is observed in 2022,

with 48.8% negative estimates. However, strong convergence is found at Q50, suggesting that similar selling behaviour was mainly followed by investors who tracked the broader market trend.

During the normalisation phase, herding is reduced at both quantiles. Negative estimates are found in only 27.0% of the rolling windows at Q10 and 11.5% at Q50. This confirms that trading decisions were again based mainly on fundamental information as macroeconomic and geopolitical uncertainty declined.

The herding identified at the lower quantiles in the pooled models should not be interpreted as evidence of herding during tranquil market conditions. It is mainly driven by crisis periods, during which low-dispersion days are concentrated. Therefore, herding in the chemical sector is better described as episodic rather than persistent.

TABLE 5: ROLLING WINDOW QUANTILE REGRESSION SUMMARY BY SUB PERIOD

Sub-Period	Mean γ_2 (Q10)	% Negative (Q10)	Mean γ_2 (Q50)	% Negative (Q50)	Inference
Chemical Supercycle (Apr 2015 - Mar 2018)	5.73	10.4%	3.35	0.8%	No herding
Sector Correction (Apr 2018 - Dec 2019)	9.08	0.0%	4.93	3.5%	No herding
COVID-19 Crisis (Jan 2020 - Mar 2021)	-0.53	76.2%	-1.35	81.0%	Herding
Recovery Phase (Apr 2021 - Dec 2021)	3.12	10.6%	-0.84	87.8%	Herding (Q50)
Geopolitical Shock (Jan 2022 - Dec 2022)	0.24	48.8%	-2.23	89.5%	Herding (Q50)
Normalisation (Jan 2023 - Mar 2025)	1.13	27.0%	3.01	11.5%	No herding

Note: Mean γ_2 is the average rolling coefficient of the squared market return term. % Negative refers to the proportion of 250-day windows in which $\gamma_2 < 0$, indicating herding. Herding inference is based on a threshold of $\geq 60\%$ negative windows. Source: Author's calculation

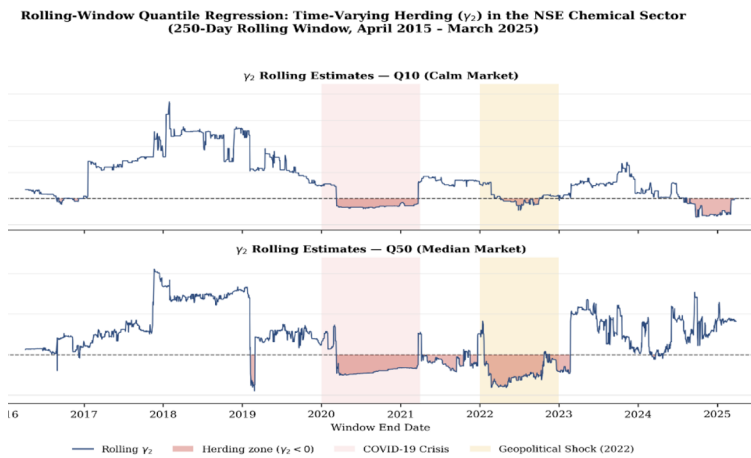


Figure 1. Rolling-Window Estimates of γ_2 at the 10th and 50th Quantiles in the NSE Chemical Sector, 2015–2025.

Note: Shaded areas denote the COVID-19 crisis (red) and the 2022 geopolitical shock (yellow). Red fill below the zero line indicates herding episodes ($\gamma_2 < 0$). Each point is dated by the end of its 250-day window. Source: Author's calculation.

5. Conclusion

Neither continuous nor structural herding is observed in the Indian chemical sector. However, it is observed at low conditional dispersion. The time-series decomposition reveals that these episodes are not distributed evenly across tranquil periods rather they concentrate in the COVID-19 crash and the 2022 commodity crisis. When market activity strengthens because of stronger upward movements, noticeable declines, or abrupt volatility, herding wanes and return dispersion broadens, evidencing greater independent decision-making. Thus, it can be said that investor behaviours are strongly influenced by the prevailing sentiment, and the sector tends to be information driven outside brief episodes of severe pessimism.

The insight for the regulators and policymakers is that the behavioural risk in this sector is not distributed across ordinary trading conditions rather it is concentrated in crisis windows. Therefore, monitoring efforts are better directed at periods of severe

macroeconomic or geopolitical shocks than at overall, continuous supervision of market-wide co-movements.

The study shows that herding in the chemical sector is occasional, asymmetric, and shaped by specific market conditions and thus contributes to the behavioural finance literature. The study is not free from limitations. The survivorship bias may be there in the sample. Daily rather than intraday data have been used in the analysis. The study fails to distinguish institutional from retail order flow. For future research, the herding behaviour in emerging markets may be studied using behavioural sentiment indicators, intraday data and investor-type classifications.

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ANNEXURE I: CONSTITUENT COMPANIES

Sr. No.	Name of Company
1	Aarti Industries Ltd.
2	Atul Ltd.

3	Bayer Cropscience Ltd.
4	Chambal Fertilizers & Chemicals Ltd.
5	Coromandel International Ltd.
6	Deepak Nitrite Ltd.
7	E.I.D. Parry (India) Ltd.
8	Gujarat Narmada Valley Fertilizers and Chemicals Ltd.
9	Himadri Speciality Chemical Ltd.
10	Linde India Ltd.
11	Navin Fluorine International Ltd.
12	PCBL Chemical Ltd.
13	PI Industries Ltd.
14	Pidilite Industries Ltd.
15	SRF Ltd.
16	Solar Industries India Ltd.
17	Tata Chemicals Ltd.

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