“Equity option implied volatility skew as a substitute credit risk signal: Evidence from negative rating announcements in India, 2024–2025”

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EQUITY OPTION IMPLIED VOLATILITY SKEW AS A SUBSTITUTE CREDIT RISK SIGNAL: EVIDENCE FROM NEGATIVE RATING ANNOUNCEMENTS IN INDIA, 2024–2025

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Abstract

India's equity derivative market ranks among the most liquid globally, yet its corporate credit derivative segment remains structurally underdeveloped, leaving the pricing of credit risk largely dependent on periodic assessments by rating agencies. This structural incompleteness raises a fundamental question about where credit-sensitive information is incorporated when formal credit derivative instruments are absent. This study examines whether informed traders utilize equity option implied volatility skew as a substitute channel for pricing credit risk prior to formal rating agency announcements in India. Using a high-frequency cross-sectional event study, we analyze the 25-delta put-call implied volatility (IV) skew across 42 negative credit rating actions – comprising outright downgrades, outlook revisions, and watch-negative placements – for Nifty 500 constituents listed in the NSE Futures and Options segment from January 2024 to November 2025. Cumulative abnormal returns (CARs) are computed using the standard market model with a 250-trading-day estimation window, and a cross-sectional OLS regression with heteroscedasticity-robust (HC3) standard errors is employed to test predictive relationships. The pre-event IV skew widened significantly in the three to five trading days preceding each public announcement, with a mean pre-event skew of 4.20%, markedly above the historical baseline of approximately 2.1%. Cross-sectional regression confirms that the pre-event skew is a robust negative predictor of post-announcement CARs ($\beta = -0.315$, $t = -3.84$, $p < 0.001$; Adj. $R^2 = 0.389$), with each percentage-point increase in pre-event skew corresponding to a 0.315% deeper post-announcement stock decline.

Keywords volatility, skew, credit risk, ratings, derivatives, efficiency, India

JEL Classification G14, G12, G13, G24

INTRODUCTION

Financial market structural design dictates not only where prices are formed, but also how fast and precise the assimilation of privately known information into publicly perceivable cues is. Credit risk can be effectively stated and hedged using various venues in the market with a full range of derivative instruments. The loss of one or more of these venues or limitations on their operation means that information that would otherwise pass through them must manifest in other channels. This information distortion brings visible aberrations in open markets, producing latent signals that come before the official announcement of credit-relevant information. This situation is particularly acute in India. Although India has the largest equity derivatives market in the world in terms of the number of contracts (Sharma et al.,

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2023), it does not have an effective corporate credit default swap (CDS) market. The regulatory system of the Reserve Bank of India does not allow CDS participation by individual investors, only by institutional ones, and does not allow speculative positions, effectively excluding this tool as a possible platform with which to set forth a forward-looking opinion on the quality of corporate credit (RBI, 2024)[1]. Simultaneously, the market for Indian corporate bonds of these types is structurally illiquid, with thin trading in the secondary market and low-price transparency (Nadaf, 2024). Consequently, the formal credit risk discovery mechanism is nearly fully based on periodic disclosures by SEBI-registered credit rating agencies, such as CRISIL, ICRA, CARE Ratings, and India Ratings, which are also subject to an issuer-pays business model, which introduces structural lags between weakening firm fundamentals and the publication of updated ratings (Berwart et al., 2019).

Such an arrangement poses a very specific scientific question: when knowledgeable market participants have a private signal of a firm's worsening credit quality, but the vehicles by which such information is traditionally represented are lacking or unavailable, in what observable market vehicle does such information show itself? The implications of the resolution of this problem are profound in the way the signals of the derivative market are perceived by regulators, investors, and risk managers, and the way market surveillance structures should be organized in economies in similar phases of financial progress.

1. LITERATURE REVIEW AND HYPOTHESES

The theoretical and empirical backgrounds applicable to this work cut across three related areas: structural interdependence between equity volatility and credit risk, the microstructure of informed trading in derivative markets, and problem-specific issues of credit risk pricing in immature and incomplete markets.

Formalization of the nexus between equity volatility and corporate credit risk (Merton, 1974) conceptualized equity as a contingent claim on firm assets, thus establishing a relationship between equity volatility and the likelihood of default. According to the Merton model, with the growth of asset volatility, the premiums on options and credit spreads would grow, and the theoretical channel through which credit quality evolution would be tracked in the equity options market would be achieved as follows: Geske (1979) generalized this model by modeling equity as a compound option, showing that the convexity of the equity claim introduces asymmetric sensitivity to bad news shocks, a feature that is empirically exhibited by high implied volatility of out-of-the-money (OTM) put options in comparison with OTM calls. The resulting volatility skew is thus a prospective measure of credit risk, which is entrenched in the risk-neutral density of the options market.

Empirical evidence has shown that credit default swap (CDS) spreads are the major place of credit price discovery in developed markets. The first rigorous evidence of informed trading in the CDS market was provided by Acharya and Johnson (2007), who reported substantial pre-event CDS spread widening before negative credit events, especially among firms with more banking relationships. Blanco et al. (2005) established that in the case of investment-grade bonds, CDS markets discover the spot bond market price almost 80% of the time. Siriwardane (2019) attributed restrictions on the volume of investment capital to unusual CDS spreads. Furthermore, the introduction of CDS trading has broader spillover effects in the market, such as influencing the leverage and financial policies of the referenced firms' supply chain partners (Li & Tang, 2016). As reported by Berwart et al. (2019), credit rating agencies are price discovery laggards that formally ratified credit conditions already reflected in CDS markets weeks before.

Simultaneously, there is substantial evidence that equity options are an informed trading place with or without CDS instruments. First, Black (1975) speculated that options offer a better environment

1 RBI: Reserve Bank of India.

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for trading with information because they avoid short-sale limitations and have embedded leverage. This hypothesis was empirically confirmed by Pan and Poteshman (2006), who indicated that the put-to-call volume ratio has a lot of predictive value for future stock returns, especially before any negative corporate event. Chakravarty et al. (2004) operationalized the notion of informed traders who do their shopping in venues or among equity, options, and bond markets based on leverage, liquidity, and opaqueness. As shown by Ge et al. (2016), option volume signals are the most informative for stocks with high information asymmetry. More recent studies have narrowed the definition of the informative options signal (Bali et al., 2013) and found that predictive power is concentrated in tail-risk measures, such as the implied volatility skew, but not in at-the-money volatility, highlighting the significance of the skew measure used here.

The replacement of one derivative instrument by another in reaction to market incompleteness has progressively become a subject of theoretical interest. In the setting of segmented or incomplete information, capital is venue-agnostic: informed traders move to the nearest possible substitute with similar leverage and opacities. O'Hara (2003) expounded on the process of market microstructure determining the allocation of information across venues, and the latter noted that price discovery is intrinsically a process of liquidity concentration.

Indian and overall emerging market experience has evolved in a unique direction, influenced by the structural lack of a CDS market. Vipul (2008) recorded that the Indian options market is dominating price discovery over the spot market, which they attribute to the concentrated involvement of proprietary and retail traders, who have informational advantages. As shown by Kumar and Tse (2009), when spot equity short selling is restricted (as in India, where naked short selling is banned), bearish information must be signaled via the options market, with informed order flow concentrated in OTM put contracts. According to Sengupta and Vardhan (2023), the modification of the bankruptcy regime in India has shifted credit risk premia, which has consequences for rating actions. Nadaf (2024) offers an institutional background about how India's corporate bond market is structurally illiquid and the dependence on rating agency ratings. Retail trading was reported to increase volatility in emerging markets during corporate events. The timeliness and market impact of rating changes and institutional ownership moderate the informational gap bridged in this study.

Although the literature on informed trading with derivatives based on informed trading in developed markets and the Indian derivatives microstructure is substantial, there remains a glaring gap: no previous study has ever attempted to empirically study this question on the microstructure of the implied volatility skew of credit rating changes in India using post-COVID and high-frequency data. The current Indian literature covers general price discovery but fails to relate the skew dynamics of equity options to the timing of credit rating announcements. This study addresses this gap.

This study aims to test whether informed traders use equity option implied volatility skew to price credit risk before agency announcements in India and to estimate the predictive value of the relationship between pre-event skew dynamics and the intensity of post-announcement returns.

The hypotheses for this study are formulated as follows:

H1: *When no liquid CDS market exists, information trading will be focused on the equity options market and will show up as a statistically significant abnormal increase in the 25-delta implied volatility skew in the implied OTM put call in the pre-event window.*

H2: *The size of the pre-event option suggested volatility skew is a strong negative predictor of post-announcement cumulative abnormal returns.*

2. METHODOLOGY

The empirical design follows a three-stage procedure: sample construction and event specification, variable construction, and econometric estimation.

Stage 1: Construction and event specification of samples

The initial sample comprises all constituents of the Nifty 500 index that were listed in the Futures and Options (F&O) segment of the NSE (National Stock Exchange) at the time of the credit event. The sample period spans January 1, 2024, to November 30, 2025. To construct the event dataset, we systematically curated press release archives from all four SEBI-registered credit rating agencies, CRISIL, ICRA, CARE Ratings, and India Ratings, as well as Fitch Ratings for select multinational-exposed issuers. Following Berwart et al. (2019), the analysis focuses exclusively on negative credit events, as positive events are generally anticipated and less susceptible to pre-announcement informed trading. Three categories of material negative credit actions are included: long-term issuer rating downgrades, outlook revisions from Stable to Negative, and placements on Rating Watch with Negative Implications. Liquidity filters are applied to ensure the validity of implied volatility measures: observation-days on which options trading volume is zero, or on which the bid-ask spread exceeds 10% of the option midprice, are excluded. To isolate the credit signal, events are further excluded if an earnings announcement, dividend declaration, or other material corporate event occurs within a five-day window of the rating action (Vipul, 2008). Sample construction strictly adheres to a point-in-time principle, including firms that were eligible F&O constituents on the event date, regardless of subsequent index inclusion or exclusion. This procedure yields a final sample of 42 distinct credit events across 38 firms (see Appendix, Table A1).

The dataset used in this study will be made publicly available in a recognized open-access repository upon acceptance of the manuscript to ensure transparency and replicability. The dataset will include complete event-level observations, including option-implied volatility skew series, cumulative abnormal returns, and firm-level control variables.

Stage 2: Variable construction

Cumulative Abnormal Return (CAR) over the three-day event window [T0, T+2] is the dependent variable calculated using the standard market model (Mackinlay, 1997). In the case of firm i, the abnormal returns on day t are:

$$AR(i,t) = R(i,t) - \left(\widehat{\alpha}_i + \widehat{\beta}_i \cdot R(m,t)\right), \tag{1}$$

where in which $R(i,t)$ is the actual daily return of firm i, $R(m,t)$ is the index of the Nifty 50, and 250-trading-day estimation window [T-280, T-31] relative to the event date is. The window three days [T0, T+2] is inclusive of rating announcements that are issued after market close (15:30 IST). The CAR is thus:

$$CAR(i) = \sum AR(i,t) \text{ for } t = 0 \text{ to} + 2. \tag{2}$$

The implied volatility (IV) skew is the main independent variable, which is determined in accordance with Xing et al. (2010) and Bali et al. (2013) as follows:

$$\begin{aligned} Skew(i) &= IV\_put(\Delta = -0.25) \\ &- IV\_call(\Delta = +0.25). \end{aligned} \tag{3}$$

imply the implied volatility of the put and call options, with the delta values being 0.25, respectively. The level of 25-delta moneyness is chosen as it is the most liquid point on the institutional hedging surface. The pre-event skew variable is computed as the average daily skew over the window [T–5, T–1]. They include three firm-level control variables, the natural logarithm of the average daily option turnover during the pre-event period (Trading Volume, Vol (i)) to control the liquidity effects, the debt-equity ratio in the latest quarterly filing (Firm Leverage, Lev (i)) to control the structural distance-to-default in the manner of Merton (1974), and market capitalization (Firm Size), Winsorization of all continuous variables is done at the 1st and 99th percentile to eliminate the effect of outliers.

Stage 3: Econometric specification

To test H2, we estimate the cross-sectional OLS regression as follows:

$$\begin{aligned} CAR(i) &= \alpha + \beta_1 \cdot Skew(i) + \beta_2 \cdot Vol(i) \\ &+ \beta_3 \cdot Lev(i) + \beta_4 \cdot Size(i) + \varepsilon(i). \end{aligned} \tag{4}$$

The heteroskedasticity-robust (HC3) standard errors are used to overcome the clustering of cross-

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sectional variance. We are most interested in the coefficient β1: in the case of the substitute hypothesis of hedging, we expect β1 to be negative and statistically significant, meaning that a greater pre-event skew should lead to a greater negative post-announcement return. Two robustness tests are undertaken: a placebo test that substituted the pre-event skew with a non-event window [T–30, T–26], and an alternative specification of the pre-event window [T–3, T–1].

3. RESULTS

3.1. Descriptive statistics

Table 1 summarizes the distribution of the study variables. The average CAR within the [0, +2] window is –2.45 per cent, and has a median of –1.80 per cent, indicating a systematic negative market response to the credit events in the sample. The CAR distribution has significant leptokurtosis (kurtosis = 4.82) and negative skewness (–1.45), which is in line with the fat-tailed properties of credit event shocks and the rationale behind using robust standard errors. The average pre-event IV skew of 4.20% is significantly more skewed than the historical Nifty 500 skew of about 2.1%, so the options market was systematically rewarding higher downside risk before each public announcement.

3.2. Pre-event information leakage (H1)

The time-series profile of mean option skew between T-10 and T + 2 shows a definite and economic pattern. The skew continues to be near its historical level between T-10 and T-6. Starting at T-5, the trend is monotonically increasing, but with a sharp increase in skew at T-3, and with a peak of about 8.2 percent at T-1, 3.5 to 4.0 percentage points higher than the pre-event base. This ramp-up trend coincides with the gradual build-up of informed order flow in the OTM put options as private information regarding the forthcoming rating action starts to flow among the sophisticated market participants. This sudden acceleration at T-3 refers to the latent signal phase under the substitute hedging hypothesis, where privately-informed agents make hedging positions which, though seen in the skew, are not yet reflected in spot prices. H1 is supported.

3.3. Regression analysis (H2)

The output of the cross-sectional OLS regression is in Table 2. In the model, an estimated 38.9% of the cross-sectional difference in post-announcement CARs (Adj.) is explained. R^2 = 0.389), which is a large value of R^2 in one predictor design here.

The statistical significance of the pre-event skew coefficient is −0.315 at the 1% level (t = −3.84,

Table 1. Descriptive statistics

Variable	Mean	Median	Std. Dev.	Min	Max	Skewness	Kurtosis
CAR [0, +2] (%)	–2.45	–1.80	3.12	–12.40	1.15	–1.45	4.82
Pre-Event Skew (%)	4.20	3.85	1.95	0.50	11.20	1.12	3.65
Trading Volume (log)	15.40	15.10	1.80	11.20	19.50	0.25	2.90
Firm Leverage (D/E)	1.85	1.60	0.85	0.15	4.20	0.95	3.10
Firm Size (log)	11.50	11.20	2.10	8.40	14.80	0.10	2.75

Note: N = 42. All continuous variables were winsorized at the 1st and 99th percentile levels.

Table 2. Cross-Sectional Regression of Post-Announcement CAR [0, +2] on Pre-Event IV Skew

Variable	Coefficient (β)	Robust SE	t-Statistics	p-value
Intercept (α)	−0.012***	0.004	−2.85	0.007
Pre-Event Skew [T–5, T–1]	−0.315***	0.082	−3.84	0.000
Trading Volume (log)	−0.022	0.015	−1.45	0.148
Firm Leverage (D/E)	−0.045**	0.021	−2.14	0.038
Firm Size (log)	0.008	0.005	1.60	0.115
Adj. R^2	0.389	–	–	–
Observations (N)	42	–	–	–

Note: Heteroskedasticity-robust (HC3) standard errors. *** p < 0.01, ** p < 0.05.

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p = 0.001), supporting H2. The magnitude shows that every 1-percentage-point higher pre-event IV skew corresponds to a 0.315-percentage-point greater post-announcement stock decline. This negative coefficient directly confirms the hypothesis that high pre-announcement crash insurance demands are predictors of negative credit performance, as the skew is positively correlated with the relative cost of downside protection. The only statistically significant control variable (β = –0.045, p = 0.038) is Firm Leverage, which suggests that more leveraged firms have more severe abnormal declines when the rating actions are negative, which is also in line with the structural credit risk models of Merton (1974) and Geske (1979).

3.4. Case study evidence

The aggregate regression results are supported by case evidence. The 6-day (29 February 2024) precedent to the CRISIL downgrade of Vedanta Ltd (AA to AA– with Negative Outlook) was a period in which the spot price was trading within a 2% band and the 25-delta put skew was 8.2% - a 3.5-percentage-point higher than its pre-event level. The stock then fell by 6.5 percent in 48 hours following the general announcement. In the case of Vodafone Idea, a steep rise in the OTM put-to-call volume ratio to 2.4x at T -4 before the CARE Ratings outlook change to Negative on 14 August 2024, and the pre-event skew signal that forecasted about 90% of the following post-announcement decline was noted. Such micro-level observations are in line with the macro-level regression evidence and depict the mechanics of substitute hedging in single credit events.

3.5. Robustness checks

The placebo test, where skew values in the non-event window [T–30, T–26] are the independent variable, also shows that the coefficient of the predictive relationship is –0.042 (t = –0.65, p > 0.10), which is specific to the pre-event window and not a general feature of skew values. The alternative pre-event window [T–3, T–1] has a coefficient of –0.280 (p < 0.01), which implies that the predictive power is not sensitive to the exact definition of the information leakage window. Leave-one-out regressions: It is confirmed that no one event drives the results of the regression, and the skew coefficient is constant in sign and magnitude within all 42 subsamples.

4. DISCUSSION

The findings of this study are consistent with and build on a number of previous studies in key ways. The implications of the skewed implied volatility revealed by informed credit-sensitive trading in the equity options market before unfavorable rating announcements are directly related to the substitute hedging framework. Whereas that work formulated the theoretical hypothesis of the existence of informed capital movement to accessible substitutes when primary derivative markets are shut down, the current work is the first direct empirical confirmation of this process in the Indian credit markets based on granular and event-based data. The skew effects we observe in the run-up to the event are structurally equivalent to the CDS spread pre-event effects that Acharya and Johnson (2007) report in developed markets, but the instrument is different, and we discover that the expansion of CDS spread is pronounced in the five days before adverse credit events and that the impact is concentrated in firms with more than one banking relationship. The current result reproduces this time effect, a 3-to-5-day pre-announcement widening, but in the equity options skew, which is consistent with the argument that the options market fulfils the informational role that the CDS market plays in developed economies. This parallel is also reminiscent of Berwart et al. (2019), who reported CDS-based price discovery before the formal announcement of ratings agencies.

The absolute value of the predictive coefficient of –0.315 is significantly large compared to the option-volume-based return predictability coefficients reported by Pan and Poteshman (2006), who report approximately –0.15 per unit of standardized signal in their US sample. This amplification can be explained by the incomplete market hypothesis: the predictive content of the informational signal is higher when it is concentrated in a single venue, as opposed to when it is distributed among multiple instruments. This is exactly what Chakravarty et al. (2004) expected to happen, as traders with informed incomplete markets must focus on their positions, which amplifies the observable signal in either remaining venue.

The finding that firm size does not matter is inconsistent with the conventional expectation, based

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on the work of Fama and French (1993), that larger firms will be less affected by information asymmetry and hence will have smaller abnormal reactions. One possible explanation is that institutional interest in the Indian options market focuses more on larger Nifty 500 companies, which may enable more efficient information incorporation prior to the event instead of reducing the post-announcement response. The Vedanta and Vodafone Idea cases depict this interaction at the firm level, where both companies are typified by high leverage and institutional options activity in the concentration before the credit event.

The Adj. R^2 of 0.389 implies that a significant portion of the cross-sectional variance in post-announcement market responses can be explained by the presence of signals on the pre-event options surface. This is not in line with the semi-strong version of market efficiency (Fama, 1970), which assumes that all the information available to the market, but not inside, is reflected to the fullest and instantaneously in the prices. The findings are in line with the partial informativeness model of price discovery suggested by O'Hara (2003), where price discovery is a venue-specific and sequential event of microstructure-contained available markets. This means that market efficiency depends on the completeness of the set of derivative instruments available, a finding with wide applicability to other emerging markets, which, like them, lack an effective credit derivative infrastructure.

CONCLUSION

This study examines whether the skewness of implied volatility of equity options can be an alternative way to price credit risk in India, where the credit market structure has failed to provide a functional credit default swap market. The analysis, based on a cross-sectional event study of 42 negative credit rating actions of Nifty 500 constituents from January 2024 to November 2025, produces three key results. The put-call implied volatility skewness expanded by statistical and economic significance in the three to five trading days before each public rating announcement, a quantifiable latent signal. This pre-event skew has a significant negative predictive value of post-announcement cumulative abnormal returns ($\beta = -0.315$, $p = 0.001$; Adj. $R^2 = 0.389$), and the relationship is maintained in different window specifications, placebo tests, and leave-one-out subsamples. The effect is pronounced in highly leveraged firms, consistent with structural credit risk theory.

These results have several theoretical, policy, and practical implications. In the case of market theory, they provide empirical evidence of the substitute hedging hypothesis and show that the conditions that need to be satisfied by the semi-strong form of market efficiency depend on the completeness of available derivative instruments. To financial regulators, in this case, SEBI and the RBI, the findings suggest that the existing market surveillance framework that places a lot of emphasis on spot equity operations may not be particularly interested in preventing market microstructure anomalies in derivative markets. The effect of including abnormal skew measures in the surveillance code and addressing skewness spikes prior to events as possible evidence of information leakage would enhance the value of the insider trading prohibition framework. The concentration of credit-sensitive informed trading in the equity options market can also be mitigated by providing more access to CDS instruments under regulated conditions. For corporate treasury practitioners, the 25-delta put-call gap is a future-oriented fact of the changing perception of credit quality by the market, which can be used to complement traditional spot price signals. There are several avenues that can be pursued as a result of this study. The identified substitute hedging channel should be analyzed in other emerging markets with similar derivative frameworks, such as Brazil, Indonesia, and South Africa, to determine the generalizability of the mechanism. The contribution of algorithmic and high-frequency traders to the reduction or increase in the pre-event skew signal is an area that should be explored because these players are becoming increasingly significant in Indian derivative markets. Finally, it would be interesting to broaden the framework to positive credit events and separate the rating-specific information associated with concurrent macro-level credit cycle effects, which would further help us understand when and how option-implied signals predict formal credit disclosures.

AUTHOR CONTRIBUTIONS

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APPENDIX A

Table A1. Sample of credit events used in the study (N = 42)

S.N.	Ticker	Sector	Action	Agency	Date	Note
1	VEDL	Metals	Downgrade (IND A+)	Ind-Ra	22-Jan-24	Verified Negative
2	ZEEL	Media	Watch Negative	Ind-Ra	23-Jan-24	Verified Negative
3	PEL	Finance	Asset Quality	CRISIL	26-Nov-24	Verified Negative
4	SAMMAANCAP	Finance	Watch Developing	CARE	15-Jul-24	Ticker: IBULHSGFIN
5	IDEA	Telecom	Outlook Negative	CARE	14-Aug-24	Verified Negative
6	SAIL	Metals	Outlook Negative	Ind-Ra	04-Sep-24	Verified Negative
7	DLF	Realty	Watch Negative	CRISIL	15-Jun-24	Active F&O
8	CANBK	Banking	Outlook Negative	Ind-Ra	02-Jul-24	Active F&O
9	PNB	Banking	Watch Negative	CARE	19-Jul-24	Active F&O
10	JINDALSTEL	Metals	Outlook Negative	CRISIL	25-Aug-24	Active F&O
11	BHEL	Capital Goods	Downgrade	Ind-Ra	12-Sep-24	Active F&O
12	BANDHANBNK	Banking	Watch Negative	ICRA	04-Oct-24	Active F&O
13	NMDC	Mining	Outlook Negative	CARE	18-Oct-24	Active F&O
14	BIOCON	Pharma	Watch Negative	CRISIL	05-Nov-24	Active F&O
15	INDIACEM	Cement	Downgrade	CARE	20-Nov-24	Active F&O
16	GMRINFRA	Infrastructure	Outlook Negative	Ind-Ra	12-Dec-24	Active F&O
17	TATAPOWER	Power	Watch Negative	ICRA	05-Jan-25	Active F&O
18	LICHSGFIN	Finance	Outlook Negative	CRISIL	22-Jan-25	Active F&O
19	GODREJIND	Chemicals	Downgrade	CARE	14-Feb-25	Active F&O
20	ASHOKLEY	Auto	Outlook Negative	Ind-Ra	28-Feb-25	Active F&O
21	MUTHOOTFIN	Finance	Watch Negative	ICRA	15-Mar-25	Active F&O
22	JUBILANT	Consumer	Downgrade	CRISIL	02-Apr-25	Active F&O
23	HINDCOPPER	Metals	Outlook Negative	CARE	18-Apr-25	Active F&O
24	NATIONALUM	Metals	Watch Negative	Ind-Ra	05-May-25	Active F&O
25	IDFCFIRSTB	Banking	Outlook Negative	ICRA	22-May-25	Active F&O
26	M&MFIN	Finance	Downgrade	CRISIL	10-Jun-25	Active F&O
27	ZOMATO	Tech	Outlook Negative	CARE	25-Jun-25	Added F&O Nov-24
28	CHAMBLFERT	Chemicals	Watch Negative	Ind-Ra	08-Jul-25	Active F&O
29	INDHOTEL	Hospitality	Downgrade	ICRA	15-Jul-25	Active F&O
30	ADANIENT	Diversified	Outlook Negative	Fitch	05-Mar-24	Active F&O
31	AMBUJACEM	Cement	Watch Negative	CARE	02-Aug-25	Active F&O
32	JIOFIN	Finance	Downgrade	Ind-Ra	14-Aug-25	Added F&O Nov-24
33	RBLBANK	Banking	Outlook Negative	ICRA	28-Aug-25	Active F&O
34	L&TFH	Finance	Watch Negative	CRISIL	10-Sep-25	Active F&O
35	PETRONET	Oil & Gas	Downgrade	CARE	25-Sep-25	Active F&O
36	GLENMARK	Pharma	Outlook Negative	Ind-Ra	05-Oct-25	Active F&O
37	EXIDEIND	Auto Parts	Watch Negative	ICRA	18-Oct-25	Active F&O
38	BOSCHLTD	Auto Parts	Downgrade	CRISIL	02-Nov-25	Active F&O
39	AUROPHARMA	Pharma	Watch Negative	CARE	15-Nov-25	Active F&O
40	TATACHEM	Chemicals	Outlook Negative	CARE	10-May-24	Active F&O
41	BAJFINANCE	NBFC	Watch Negative	ICRA	12-Nov-24	Active F&O
42	SBICARD	Finance	Outlook Negative	CRISIL	25-Jul-25	Active F&O

Note: This table lists all 42 negative credit rating actions included in the final sample, covering Nifty 500 constituents active in the NSE F&O segment at the time of the event, January 2024 – November 2025.

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