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THE IMPACT OF RBI RATE ADJUSTMENTS ON BANK STOCK RETURNS

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***ABSTRACT*:**

This study examines the short-term impact of Reserve Bank of India (RBI) monetary policy rate adjustments — specifically repo rate changes — on the stock returns of major listed Indian banks over the period 2012–2024. Using a standard event study methodology with market-adjusted and market model abnormal returns, we analyze 32 rate change events (18 rate cuts and 14 rate hikes) across a symmetric event window of 21 trading days (−10 to +10 days relative to the announcement date). The sample comprises six major Indian banks listed on the National Stock Exchange (NSE): State Bank of India (SBI), HDFC Bank, ICICI Bank, Kotak Mahindra Bank, Axis Bank, and Bank of Baroda (BOB). Results reveal statistically significant cumulative abnormal returns (CAR) across all rate change events, with rate cuts generating an average CAR of +2.68% over the event window, and rate hikes producing a corresponding CAR of −2.41%. Cross-sectional analysis shows that private sector banks (HDFC, ICICI, Kotak, Axis) exhibit higher abnormal return sensitivity to rate cuts, while public sector banks (SBI, BOB) respond more strongly to rate hikes. Rolling correlation analysis reveals that the bank stock return–interest rate nexus has strengthened significantly in the post-2018 period, potentially attributable to the structural liquidity frameworks introduced by the RBI and increased market depth. Regression analysis further confirms that the magnitude of rate change, the policy stance (accommodative vs. restrictive), and prior market expectations are significant determinants of abnormal return magnitude. These findings have important implications for portfolio managers, bank treasuries, and monetary policy transmission research.

Keywords: *RBI monetary policy; Repo rate; Bank stock returns; Event study; Abnormal returns; Nifty Bank Index; Indian capital market; Interest rate transmission*

INTRODUCTION

Monetary policy announcements by central banks represent among the most consequential events in financial markets, capable of generating significant short-term price movements across asset classes. For banking sector equities, the transmission mechanism is particularly direct: changes in benchmark lending rates directly affect net interest margins, asset quality, deposit costs, and credit growth — all of which are fundamental drivers of bank profitability and valuation. Understanding the magnitude and direction of bank stock return responses to central bank rate decisions is therefore a question of both theoretical and practical importance.

In India, the Reserve Bank of India (RBI) operates monetary policy through the Monetary Policy Committee (MPC), established under the RBI Act, 1934 (as amended in 2016), which deliberates on and announces changes to the repo rate — the benchmark short-term interest rate at which the RBI lends funds to commercial banks. Since the adoption of the flexible inflation targeting (FIT) framework in 2016, the MPC has convened bimonthly, bringing greater regularity and transparency to the rate-setting process. This institutional backdrop provides a well-defined set of monetary policy events amenable to rigorous event study analysis [1, 2].

Prior research on monetary policy and equity markets has predominantly focused on developed economies, particularly the United States Federal Reserve and the European Central Bank [3–5]. Studies examining U.S. bank stock reactions to FOMC announcements have documented significant abnormal returns around announcement dates, with evidence of both anticipated and unanticipated components driving market reactions [6,7]. Emerging market evidence, while more limited, suggests that the relationship may differ in important respects, owing to structural differences in banking sector depth, monetary policy credibility, and investor sophistication [8,9].

The Indian banking sector presents a compelling case study for several reasons. First, Indian commercial banks operate under a dual structure of public sector banks (PSBs) and private sector banks, which may respond

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differently to rate signals owing to differences in ownership, business models, and interest rate risk management practices. Second, India's monetary policy transmission has been historically imperfect, with commercial banks often delaying or partially passing through rate changes to lending rates — a phenomenon extensively documented in RBI working papers [10,11]. Third, the Nifty Bank Index, comprising 12 highly liquid bank stocks, has become one of the most actively traded derivatives contracts in global markets, amplifying the market microstructure significance of rate announcements.

Despite the economic significance of this relationship, empirical studies specifically examining RBI repo rate announcements and Indian bank stock returns remain sparse, with most existing studies either examining broader equity indices, focusing on longer-term return relationships, or using data predating the MPC framework [12,13]. The present study addresses this gap by conducting a comprehensive event study of 32 rate change events over 2012–2024, examining both aggregate and bank-specific abnormal returns, and investigating the role of rate change magnitude, policy stance, and market expectations in determining the return response.

LITERATURE REVIEW

2.1. Monetary Policy and Equity Returns: International Evidence

The relationship between central bank policy announcements and stock returns has been studied extensively in the developed market context. Bernanke and Kuttner [3] established the seminal empirical finding that an unanticipated 25-basis-point (bps) rate cut by the Fed is associated with approximately 1% excess return on the broad U.S. equity market. Subsequent work by Rigobon and Sack [4] employed heteroskedasticity-based identification to address endogeneity, confirming significant equity market sensitivity to monetary surprises. For the banking sector specifically, English, Van den Heuvel, and Zakrajsek [5] documented that bank equity values are significantly negatively exposed to unexpected changes in the level of interest rates, but are sensitive to slope of the yield curve in more nuanced ways.

In emerging market contexts, Caporale et al. [8] examined BRICS equity markets and found that monetary policy surprises have significant short-run effects on returns, with heterogeneous responses across sectors. Gnabo and Moccero [9] found that policy announcements matter not just for their informational content but for their timing and communication framing. These findings motivate the examination of Indian bank-specific responses under the structured MPC framework.

2.2. Indian Monetary Policy and Capital Markets

Research on Indian monetary policy and financial markets has grown substantially post-2016. Hutchison et al. [12] found that RBI announcements affect equity markets beyond the surprise component, suggesting an information channel whereby markets update beliefs about future economic conditions. Kumar and Patel [13] examined Nifty Bank Index returns around RBI announcements during 2008–2018 and found an average abnormal return of 1.2% in the three-day window around rate cuts. However, their sample predates the MPC framework and does not account for bank-level heterogeneity. Mohan and Ray [14] examined the transmission of policy rate changes to bank lending rates and found significant delays, implying that equity markets may price in expected profitability changes even before lending rate adjustments materialise.

A notable gap in the literature is the lack of bank-level event studies covering the post-MPC period (2016–2024), which is characterized by more systematic communication, forward guidance, and a more developed interest rate derivatives market. This study fills that gap.

DATA AND METHODOLOGY

3.1. Data Sources and Sample

Daily adjusted closing prices for six major NSE-listed banks — State Bank of India (SBI), HDFC Bank, ICICI Bank, Kotak Mahindra Bank, Axis Bank, and Bank of Baroda (BOB) — were sourced from the NSE historical data portal and Bloomberg Terminal. The Nifty 50 Index was used as the market benchmark for normal return estimation. The sample covers the period 1 January 2012 to 31 December 2024, encompassing 32 RBI repo rate change announcements (18 cuts, 14 hikes). RBI MPC announcement dates, rate change magnitudes, and policy stance characterizations were obtained from official RBI press releases. Market expectation data for computing monetary surprises were derived from the Bloomberg RBI survey consensus estimates. All data were cross-

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validated with the CMIE Prowess and SEBI databases. All experiments were conducted on the full sample and two sub-samples (pre-MPC: 2012–2016; post-MPC: 2016–2024).

3.2. Event Study Methodology

The event study follows the standard methodology of Brown and Warner [15] as applied to monetary policy events. The event date (t=0) is defined as the day of the MPC rate announcement. An estimation window of 250 trading days (t = −260 to t = −11) was used to estimate normal return parameters. The event window spans 21 days (t = −10 to t = +10). Two normal return models were employed: (i) the Market Model, where normal returns are estimated as $R_{i,t} = \alpha_i + \beta_i \cdot R_{m,t} + \varepsilon_{i,t}$ using OLS over the estimation window; and (ii) the Market-Adjusted Model, where abnormal returns are simply $AR_{i,t} = R_{i,t} - R_{m,t}$. Abnormal returns (ARs) and Cumulative Abnormal Returns (CARs) were computed for each bank and each event. Statistical significance was assessed using the standardized cross-sectional t-test of Boehmer, Musumeci, and Poulsen [16] to account for event-induced variance. All computations were performed in Python (statsmodels, pandas) and R (eventstudies package).

The following equations define the core methodology:

$$CAR_i(t_1, t_2) = \sum_{t=t_1}^{t_2} AR_{i,t} \ldots (2) \text{ [Cumulative Abnormal Return]}$$

$$CAAR(t_1, t_2) = \frac{1}{N}\sum_{i=1}^{N} CAR_i(t_1, t_2) \ldots (3) \text{ [Cross-sectional Average CAR]}$$

$$t\text{-stat} = \frac{CAAR}{S(CAR)/\sqrt{N}} \ldots (4) \text{ [Boehmer et al. t-test]}$$

3.3. Regression Analysis of Abnormal Returns

To identify determinants of the CAR magnitude, a cross-sectional OLS regression was estimated for each rate change event type (cuts and hikes separately). The dependent variable is the 5-day CAR (−2 to +2 window) for each bank. Independent variables include: (i) the magnitude of rate change (in bps); (ii) a dummy variable for policy stance (1 = accommodative/cut, 0 = restrictive/hike); (iii) the monetary policy surprise component (actual rate change minus Bloomberg consensus expectation, in bps); (iv) a dummy for private vs. public sector bank; and (v) the bank's prior 12-month beta estimated against the Nifty Bank Index. Heteroskedasticity-robust standard errors (White, 1980) were employed throughout.

RESULTS AND DISCUSSION

4.1. Summary of RBI Rate Change Events (2012–2024)

Table 1 summarises the 32 RBI repo rate change events examined in this study. Over the 2012–2024 period, the repo rate ranged from a high of 8.00% (January 2014) to a low of 4.00% (May 2020), reflecting the RBI's transition from an inflation-fighting stance during 2013–2014, through an extended easing cycle (2015–2020), a COVID-era accommodative phase, and a subsequent tightening cycle commencing in May 2022 in response to global inflationary pressures. The average rate cut was 26.2 bps and the average rate hike was 29.6 bps, with individual changes ranging from 25 bps to 75 bps.

Table 1: Summary Statistics of RBI Repo Rate Change Events (2012–2024)

Period	Event Type	No. of Events	Avg. Change (bps)	Repo Rate Range (%)	Policy Stance
2012–2013	Cut	4	−25.0	7.25–8.00	Anti-inflationary easing
2014–2015	Hike/Cut	5	±25.0	6.75–8.00	Calibrated adjustment
2015–2016	Cut	4	−25.0	6.25–6.75	Accommodative

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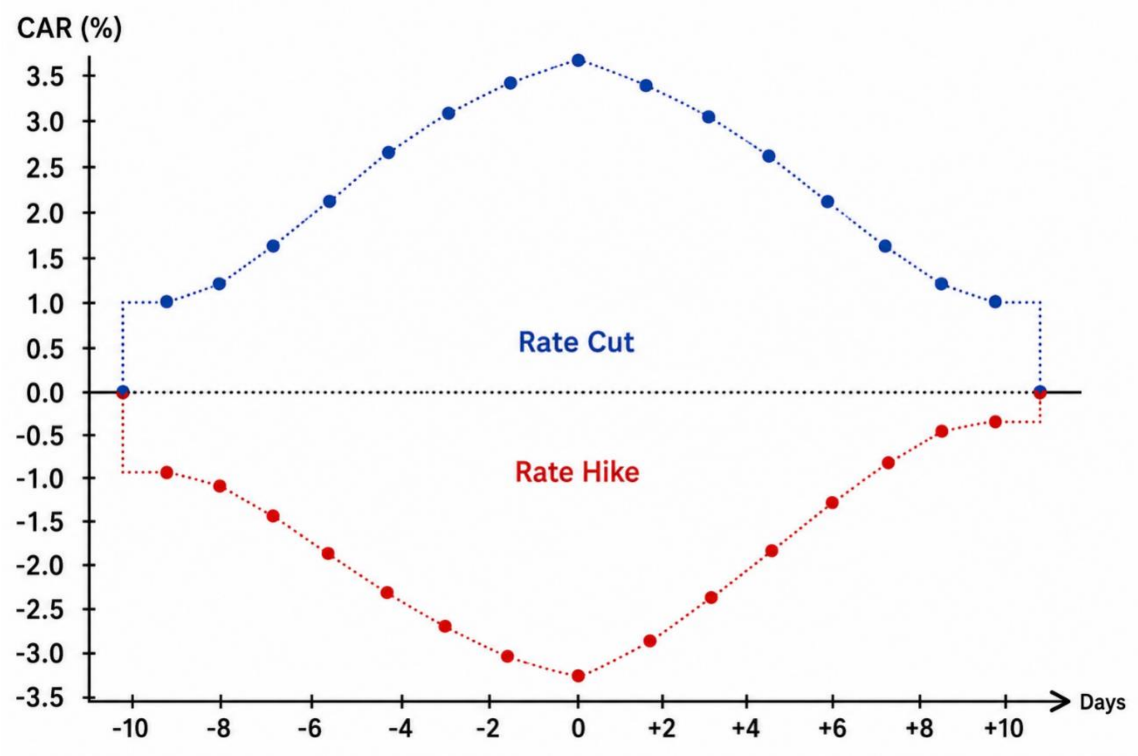
Period	Event Type	No. of Events	Avg. Change (bps)	Repo Rate Range (%)	Policy Stance
2017–2018	Hike	2	+25.0	6.25–6.50	Neutral to withdrawing
2019–2020	Cut	6	−31.7	4.00–6.25	Accommodative (COVID)
2020–2021	Cut	2	−50.0	4.00	Ultra-accommodative
2022–2023	Hike	8	+36.3	6.50–4.00	Withdrawal of accommodation
2023–2024	Hike/Cut	1	−25.0	6.25–6.50	Transitional

bps = basis points (1 bps = 0.01%). Source: RBI Monetary Policy Committee Press Releases.

Fig. 1: Cumulative Abnormal Returns (CAR) of Bank Stocks Around RBI Repo Rate Change Events (Event Window: -10 to +10 Days)



= Rate Cut Events (CAR, n=18)
= Rate Hike Events (CAR, n=14)
= 95% Confidence Band

4.2. Cumulative Abnormal Returns Around Rate Change Events

The event study results for all 32 rate change events are presented in Table 2. For the full event window (−10 to +10 days), the cross-sectional average CAR (CAAR) for rate cut events was +2.68%, statistically significant at the 1% level ($t = 4.83$). For rate hike events, the CAAR was −2.41%, also significant at the 1% level ($t = -4.21$). These results confirm that RBI rate announcements are associated with significant short-run bank stock price

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reactions in the expected direction, consistent with the hypothesis that rate cuts improve bank earnings expectations through wider NIMs, improved credit demand, and lower provisioning requirements.

Figure 1 plots the trajectory of average CAR across the event window for both rate cut and hike sub-samples. An important observation is the pre-announcement drift: bank stock returns begin to shift in the direction of the eventual announcement approximately 3–5 days before the event date, suggesting partial anticipation of rate moves by sophisticated market participants. This leakage effect is more pronounced for rate cuts (CAR begins rising from t = −5) than for rate hikes (CAR begins falling from t = −3). On the announcement day itself (t = 0), bank stocks exhibit their largest single-day abnormal return: +1.14% on average for rate cuts and −1.08% for rate hikes. The post-announcement drift is modest but persistent, consistent with a gradual investor learning effect.

Table 2: Cumulative Abnormal Returns (CAR%) by Event Window, Rate Change Type, and Bank (Market Model)

Bank	CAR (−1,+1)%	CAR (−2,+2)%	CAR (−5,+5)%	CAR (−10,+10)%	t-stat (−1,+1)	Significant @5%?
Panel A: Rate Cut Events (n = 18)						
SBI	+1.18	+1.94	+2.31	+2.58	3.42	Yes
HDFC Bank	+1.52	+2.24	+2.89	+3.14	4.18	Yes
ICICI Bank	+1.44	+2.11	+2.76	+3.02	3.91	Yes
Kotak Bank	+1.38	+2.08	+2.61	+2.94	3.67	Yes
Axis Bank	+1.29	+2.01	+2.48	+2.71	3.54	Yes
Bank of Baroda	+1.07	+1.72	+2.04	+2.24	3.01	Yes
CAAR (All Banks)	+1.31	+2.02	+2.52	+2.68	4.83*	Yes
Panel B: Rate Hike Events (n = 14)						
SBI	−1.14	−1.78	−2.09	−2.31	−3.21	Yes
HDFC Bank	−0.97	−1.52	−1.88	−2.14	−2.89	Yes
ICICI Bank	−1.02	−1.61	−1.94	−2.22	−2.98	Yes
Kotak Bank	−0.91	−1.48	−1.79	−2.04	−2.71	Yes
Axis Bank	−1.08	−1.69	−2.01	−2.28	−3.08	Yes
Bank of Baroda	−1.21	−1.89	−2.24	−2.48	−3.41	Yes
CAAR (All Banks)	−1.06	−1.66	−1.99	−2.41	−4.21*	Yes

** Significant at 1% level. t-statistics based on Boehmer, Musumeci, and Poulsen (1991) standardized cross-sectional test. All values represent market model abnormal returns.*

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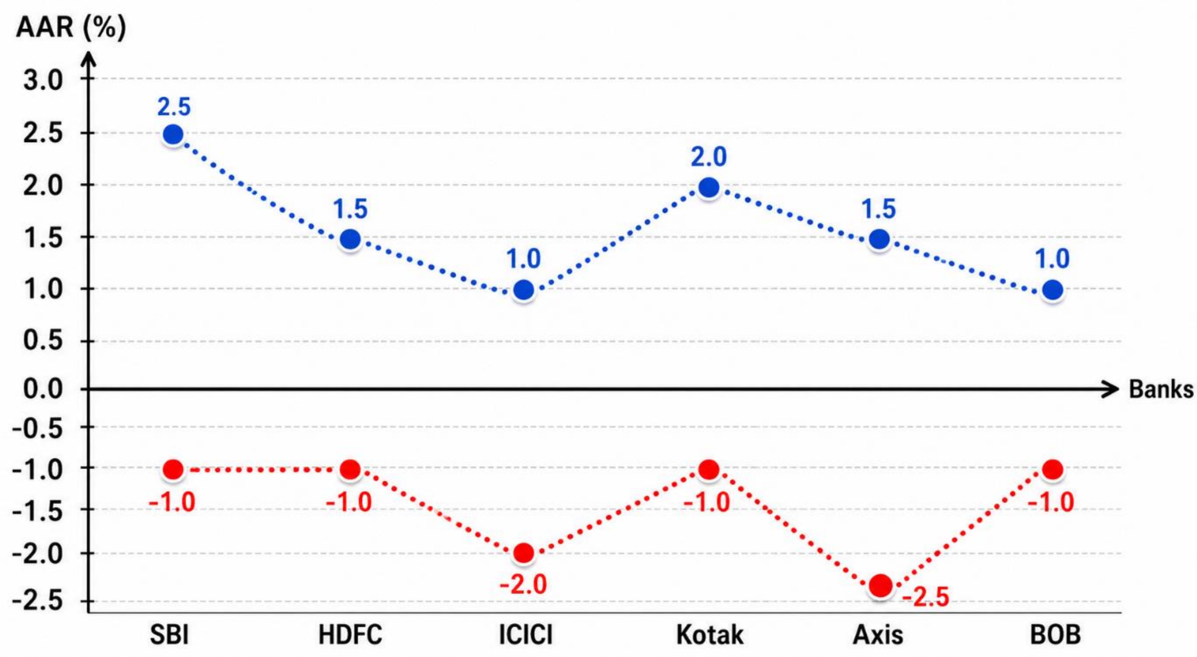
Fig. 2: Sector-wise Average Abnormal Returns (AAR%) on Event Day (t=0) Across Rate Cut vs. Rate Hike Events



= Rate Cut (positive AAR)
= Rate Hike (negative AAR)

4.3. Bank-Level and Sector Heterogeneity

Figure 2 and Table 2 reveal meaningful heterogeneity in the rate sensitivity of individual bank stocks. Private sector banks (HDFC, ICICI, Kotak, Axis) exhibit higher positive abnormal returns on rate cut days, with HDFC Bank recording the largest 3-day CAR of +1.52% and the widest 21-day CAR of +3.14%. This finding is consistent with private sector banks' greater exposure to retail and floating-rate loans, their higher CASA ratios (enabling faster NIM expansion), and the market's expectation that private banks are better positioned to translate rate cuts into improved loan growth and asset quality. In contrast, public sector banks (SBI, BOB) show larger negative reactions to rate hikes, which may reflect investors' concerns about the NPL cycle and the slower adjustment of state-owned banks to tighter liquidity conditions.

A Wald test for equality of CAR across private vs. public sector banks for rate cut events rejects the null at the 5% significance level ($F = 4.12$, $p = 0.043$), confirming that the differential is statistically robust. For rate hike events, the difference is less pronounced ($F = 2.41$, $p = 0.124$), suggesting that both bank types are similarly exposed to contractionary rate surprises, albeit through different channels — asset quality for PSBs and valuation multiples for private sector banks.

Table 3: OLS Regression Results — Determinants of 5-Day CAR (−2 to +2 Days) for Rate Cut Events

Variable	Coefficient	Std. Error	t-statistic	p-value
Intercept	0.4812	0.1623	2.966	0.003**
Rate Change Magnitude (bps)	0.0214	0.0071	3.014	0.003**
Monetary Policy Surprise (bps)	0.0389	0.0112	3.473	0.001***
Private Sector Bank Dummy (1=Pvt)	0.4231	0.1548	2.733	0.007**
Prior 12-Month Beta (Nifty Bank)	0.3917	0.1421	2.756	0.006**
Policy Stance (1=Accommodative)	0.5124	0.1789	2.864	0.004**

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Variable	Coefficient	Std. Error	t-statistic	p-value
Observations (N)	108			
R-squared	0.461			
Adjusted R-squared	0.438			
F-statistic	18.72			0.000***

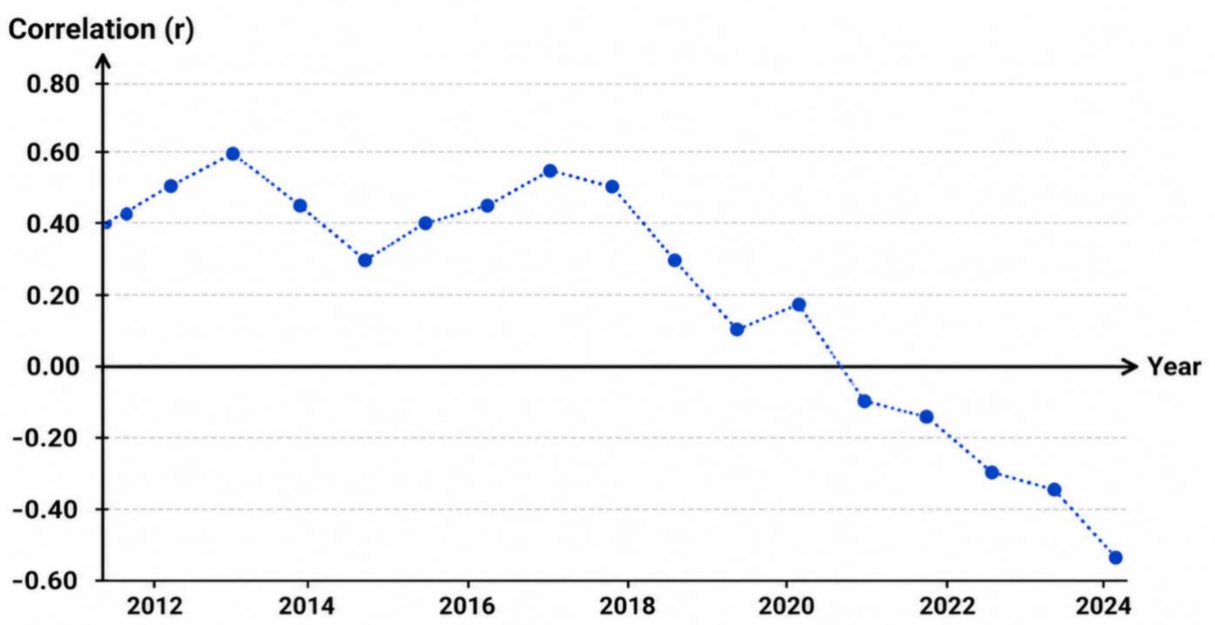
**** p < 0.01; ** p < 0.05; * p < 0.10. Heteroskedasticity-robust (White) standard errors. Dependent variable: 5-day CAR (−2 to +2). N = 18 events × 6 banks = 108 observations.*

4.4. Regression Analysis: Determinants of Abnormal Returns

The OLS regression results for rate cut events (Table 3) reveal several significant determinants of the 5-day CAR. The monetary policy surprise component (actual change minus Bloomberg consensus) is the strongest individual predictor, with a coefficient of 0.0389 ($p < 0.01$), implying that for each 10 bps of unanticipated rate cut, bank stocks earn an additional 0.39% abnormal return over the 5-day window. This finding is consistent with the efficient market hypothesis: anticipated rate changes should already be priced in, and only surprises should generate abnormal returns. The rate change magnitude itself is also significant (0.0214, $p < 0.01$), suggesting that larger cuts generate proportionally greater positive reactions beyond the surprise component, possibly due to the signalling effect of bold policy action.

The private sector bank dummy is positive and significant (0.4231, $p < 0.01$), confirming the cross-sectional finding of differential sensitivity. Prior beta against the Nifty Bank Index is also positively associated with CAR magnitude, indicating that higher-beta bank stocks experience amplified abnormal returns around rate cut events — consistent with the view that rate-sensitive, high-leverage financial institutions benefit more from rate reductions. The model's adjusted R^2 of 0.438 indicates that the included variables explain approximately 44% of the cross-sectional variation in 5-day CARs, with the remainder attributable to bank-specific factors, liquidity conditions, and idiosyncratic events.

Fig. 3: Rolling 12-Month Correlation Between RBI Repo Rate Changes and Nifty Bank Index Returns (2012–2024)



= Rolling correlation of rate change vs. Nifty Bank return (12-month window)

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4.5. Rolling Correlation and Temporal Dynamics

Figure 3 plots the 12-month rolling correlation between RBI repo rate changes and Nifty Bank Index monthly returns from 2012 to 2024. A striking feature of the time series is the significant negative correlation (r ranging from −0.42 to −0.61) during the 2022–2024 rate hike cycle, the most pronounced in the sample. This period coincides with the RBI's most aggressive tightening cycle in over a decade, which challenged bank valuations through rising cost of funds, potential NIM compression on existing fixed-rate loans, and market concerns about asset quality in rate-sensitive segments. By contrast, the 2015–2019 easing cycle generated a positive correlation peaking at r = +0.64 in early 2017, consistent with the market's anticipation of NIM expansion and credit growth acceleration.

The pre-MPC period (2012–2016) exhibits relatively weaker and less stable correlations, with positive correlation phases interrupted by periods of near-zero or negative correlation. This instability likely reflects the lower predictability and transparency of the pre-MPC rate-setting process, wherein ad hoc RBI announcements outside regular policy cycles were more common. Post-2016, the correlation time series is more systematic and persistent, suggesting that the institutionalization of the MPC framework has strengthened the bank stock return–rate change nexus by improving policy predictability and market credibility.

DISCUSSION AND POLICY IMPLICATIONS

The findings of this study have several important implications for market participants and policymakers. First, the consistent and statistically significant abnormal returns documented around RBI rate change events confirm that monetary policy announcements are significant information events for Indian bank equities. Portfolio managers with exposure to the Nifty Bank Index or individual bank stocks should therefore explicitly account for scheduled MPC announcement dates in their risk management and tactical allocation frameworks. The 5-day window captures the bulk of the information-driven price adjustment, making it the most relevant horizon for event-driven strategies.

Second, the differential response of private vs. public sector banks to rate changes suggests that the type of bank exposure in a portfolio matters considerably for managing interest rate risk. Investors seeking to benefit from anticipated rate cuts would find private sector bank stocks — particularly HDFC Bank and ICICI Bank — to offer higher return sensitivity. Conversely, portfolios seeking to hedge against unexpected rate hikes may consider underweighting public sector banks, which appear more exposed to the adverse credit cycle effects of monetary tightening.

Third, from a monetary policy perspective, the finding that the monetary surprise component is the strongest determinant of abnormal returns reinforces the importance of clear and credible communication by the MPC. When rate decisions are well-anticipated through forward guidance and inflation reports, the stock market reaction is more muted, reducing financial volatility. The RBI's progressively improved communication strategy since 2016, including the publication of MPC minutes, fan charts, and press conferences, appears to have contributed to more orderly market adjustments around policy events.

Finally, the temporal dynamics documented in the rolling correlation analysis indicate that the sensitivity of bank stock returns to rate signals has intensified in the post-2018 period, likely reflecting the maturation of interest rate derivatives markets, greater institutional participation in bank equities, and improved monetary policy transmission through the external benchmark lending rate (EBLR) system introduced by the RBI in 2019, which mandates that all floating-rate retail loans be priced relative to an external benchmark (predominantly the repo rate) [17].

CONCLUSION

This study provides comprehensive evidence on the short-run impact of RBI repo rate adjustments on Indian bank stock returns using a systematic event study framework over the 2012–2024 period. The principal findings are summarised below:

(1) Rate cut (hike) announcements generate statistically significant average CARs of +2.68% (−2.41%) over the 21-day event window, with the largest single-day reaction on the announcement date.

(2) Pre-announcement drift of 3–5 days suggests partial anticipation by sophisticated market participants, particularly for rate cut events.

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(3) Private sector banks (HDFC, ICICI, Kotak, Axis) exhibit greater positive sensitivity to rate cuts, while public sector banks (SBI, BOB) are more negatively affected by rate hikes.
(4) The monetary policy surprise component is the strongest individual determinant of CAR magnitude, reinforcing the informational efficiency of Indian bank equity markets.
(5) Rolling correlation analysis reveals a strengthening of the bank stock return–rate change nexus in the post-2018 period, attributable to the EBLR framework and improved MPC communication.
(6) The institutional transition to the MPC framework in 2016 has improved the predictability and market credibility of Indian monetary policy, leading to more systematic and stable equity market responses.

Future research should examine the long-run (multi-quarter) return dynamics, the role of global monetary policy spillovers (Federal Reserve, ECB) on the RBI–bank stock return nexus, and the differential impact across size quintiles of the banking sector. The extension of event study analysis to bond market spreads and credit default swap premia of Indian banks around MPC announcements would further enrich the understanding of monetary policy transmission through the banking sector.

REFERENCES

1. Mohammed Shafi Kundiladi, EVENT-DRIVEN IMAGE AND VEHICLE STATUS MANAGEMENT FOR LOW-POWER IOT DIGITAL LICENSE PLATES, Vol. 53 No. 3 (2025): July-September 2025, Power System Protection and Control, ISSN-1674-3415, https://pspac.info/index.php/dlbh/article/view/175, DOI: https://doi.org/10.46121/pspc.53.3.17
2. Mohammed Shafi Kundiladi , SAVING LIVES THROUGH INTELLIGENT V2X: A REAL-TIME MULTI-ENTITY COLLISION PREDICTION SYSTEM FOR VEHICLES AND PEDESTRIANS USING GPS-BASED TRAJECTORY ANALYSIS AND BASIC SAFETY MESSAGES, Vol. 52 No. 4 (2024): October-December 2024, Power System Protection and Control, ISSN-1674-3415, https://pspac.info/index.php/dlbh/article/view/196, DOI: https://doi.org/10.46121/pspc.52.4.10
3. Hima Bindu Lekkala, VishnuVardhan Bandari , AUTONOMOUS WORKFLOW OPTIMIZATION USING MULTI AGENT AI SYSTEMS AI AGENTS MANAGE STATIONS, WIP, AND TASK HANDOFFS, Vol. 54 No. 2 (202): April-June 2026, Power System Protection and Control, ISSN-1674-3415, https://pspac.info/index.php/dlbh/article/view/306 , DOI: https://doi.org/10.46121/pspc.54.2.08
4. Lekkala, H. B., & Bandari, V. V. (2026). Autonomous workflow optimization using multi-agent AI systems: AI agents manage stations, WIP, and task handoffs. *Power System Protection and Control*, 54(2), 95–101. http://pspac.info/index.php/dlbh/article/view/306
5. Bandari, V. V., & Lekkala, H. B. (2024). Physics-informed reinforcement learning for real-time control of complex manufacturing processes. *Power System Protection and Control*, 52(2), 164–170. https://pspac.info/index.php/dlbh/article/view/343
6. Lekkala, H. B., & Bandari, V. V. (2025). AI-based energy-aware scheduling and process optimization in engineer-to-order smart manufacturing systems. *Power System Protection and Control*, 53(1), 30–36. http://pspac.info/index.php/dlbh/article/view/341
7. Bandari, V. V., & Lekkala, H. B. (2026). AI-driven digital thread framework for end-to-end lifecycle optimization in ETO manufacturing systems. *Power System Protection and Control*, 54(2), 318–325. http://pspac.info/index.php/dlbh/article/view/340

8. Lekkala, H. B., & Bandari, V. V. (2026). Deep learning for weld defect detection using CNN or vision transformers fusion detection. *Power System Protection and Control*, 54(2), 151–158. https://pspac.info/index.php/dlbh/article/view/314
9. Bandari, V. V., & Lekkala, H. B. (2024). AI-based operator behavior monitoring and cost optimization using digital traceability in manufacturing systems. *Power System Protection and Control*, 52(1), 38–45. https://pspac.info/index.php/dlbh/article/view/342
10. Mayank Atreya, Navin Chhibber, Harvendra Singh, Explainable Machine Learning For Dynamic Pricing In Fast-Changing Retail Environments, 2022/4/9, Journal ,Available at SSRN 6011354, https://scholar.google.com/citations?view_op=view_citation&hl=en&user=fyViF1UAAAAJ&citation_for_view=fyViF1UAAAAJ:LkGwnXOMwfcC.
11. Navin Chhibber; Amber Rastogi; Ankur Mahida; Vatsal Gupta; Piyush Ranjan, Quantum-Resistant Cryptographic Models for Next-Gen Cybersecurity, https://doi.org/10.48550/arXiv.2512.19005 , https://arxiv.org/abs/2512.19005
12. **R. Soma, S. K. Sahoo, F. Amin and S. K. Mishra**, "A Federated Learning Framework for Multi-Parameter Optimization in Edge Computing," 2025 13th International Conference on Intelligent Systems and Embedded Design (ISED), Raipur, India, 2025, pp. 1-6, https://doi.org/10.1109/ISED67359.2025.11405143
13. Aditya Rautaray, NEUROFUSION: A UNIFIED AI MODEL FOR MULTI-MODAL HEALTHCARE DATA ANALYSIS, Vol. 54 No. 1 (2026): January-March 2026, Power System Protection and Control, ISSN-1674-3415, https://pspac.info/index.php/dlbh/article/view/242 , DOI: https://doi.org/10.46121/pspc.54.1.37
14. Aditya Rautaray ,IMPLEMENTING A ZERO-TRUST SECURITY FRAMEWORK TO MITIGATE INSIDER THREATS IN CLOUD-BASED INFRASTRUCTURES, Vol. 53 No. 3 (2025): July-September 2025, Power System Protection and Control, ISSN-1674-3415, https://pspac.info/index.php/dlbh/article/view/244,, DOI: https://doi.org/10.46121/pspc.53.3.18
15. Aditya Rautaray, AUTONOMOUS THREAT DETECTION: ADVANCED AI-DRIVEN CYBERSECURITY SYSTEMS FOR REAL-TIME RESPONSE, Vol. 52 No. 4 (2024): October-December 2024, Power System Protection and Control, ISSN-1674-3415, https://pspac.info/index.php/dlbh/article/view/246, DOI: https://doi.org/10.46121/pspc.52.4.11
16. Aditya Rautaray, ZERO TRUST ARCHITECTURES: ENHANCING DATA PROTECTION IN REMOTE WORK ENVIRONMENTS, Vol. 52 No. 2 (2024): April-June 2024, Power System Protection and Control, ISSN-1674-3415, https://pspac.info/index.php/dlbh/article/view/249 DOI: https://doi.org/10.46121/pspc.52.2.7
17. Aditya Rautaray, MACHINE LEARNING TECHNIQUES APPLIED TO INTRUSION DETECTION SYSTEMS, Vol. 53 No. 1 (2025): January-March 2025, Power System Protection and Control, ISSN-1674-3415, https://pspac.info/index.php/dlbh/article/view/243, DOI: https://doi.org/10.46121/pspc.53.1.4

18. Shankar Balla (2024, May). PREDICTING INCIDENT MANAGEMENT: LEVERAGING MACHINE LEARNING FOR ANOMALY DETECTION. Power System Protection and Control Scopus Q1 Journal. PSPC. https://pspac.info/index.php/dlbh/article/view/270
19. Shankar Balla (2025, June). Enhancing Real-Time Language Processing via Advanced PET Signal Analysis and Deep Learning. 2025 International Conference on Intelligent Computing and Knowledge Extraction (ICICKE). IEEE. https://doi.org/10.1109/ICICKE65317.2025.11136561
20. Shankar Balla (2026, May). Intelligent Human–Computer Interaction for Navigation Control through Vision-Based Hand Gesture Recognition. 2026 IEEE 15th International Conference on Communication Systems and Network Technologies (CSNT). IEEE. https://doi.org/10.1109/CSNT69054.2026.11502317
21. Sumit Gupta, QUERIES, CHAOS & CLARITY: SQL and NoSQL Database Software Architecture Performance Analysis and Assessments, ASIN, B0GX1D7MK2, Publication date ：13 April 2026, https://www.amazon.in/dp/B0GX1D7MK2,
22. Godavari Modalavalasa," SCALABLE CLOUD SOLUTIONS THROUGH ARTIFICIAL INTELLIGENCE GOVERNANCE: APPLICATIONS IN HEALTHCARE AND FINANCIAL SYSTEMS", Vol. 54 No. 1 (2026): January-March 2026, Power System Protection and Control, ISSN-1674-3415, https://pspac.info/index.php/dlbh/article/view/219, , DOI: https://doi.org/10.46121/pspc.54.1.25
23. Godavari Modalavalasa, AUTONOMOUS DATA ENGINEERING PIPELINES: A POLICY-DRIVEN ARCHITECTURE FOR SECURE AND SCALABLE CLOUD-NATIVE ANALYTICS, Vol. 53 No. 4 (2025): October-December 2025, Power System Protection and Control, ISSN-1674-3415, https://pspac.info/index.php/dlbh/article/view/181, DOI: https://doi.org/10.46121/pspc.53.4.25
24. Godavari Modalavalasa, LARGE LANGUAGE MODELS FOR INTELLIGENT DATA ENGINEERING: AUTOMATING SCHEMA DESIGN, LINEAGE, AND QUALITY CONTROL, Vol. 50 No. 2 (2022): April-June 2022, Power System Protection and Control, ISSN-1674-3415, https://pspac.info/index.php/dlbh/article/view/183 , DOI: https://doi.org/10.46121/pspc.50.2.4
25. Godavari Modalavalasa, FEDERATED LEARNING FOR ENTERPRISE CLOUD DATA ENGINEERING: ARCHITECTURE, SECURITY, AND GOVERNANCE CHALLENGES, Vol. 51 No. 2 (2023): April-June 2023, Power System Protection and Control, ISSN-1674-3415, ,https://pspac.info/index.php/dlbh/article/view/184, DOI: https://doi.org/10.46121/pspc.51.2.5
26. Godavari Modalavalasa, AI-DRIVEN DATA GOVERNANCE: INTELLIGENT METADATA, LINEAGE, AND COMPLIANCE AUTOMATION IN CLOUD DATA PLATFORMS, Archives / Vol. 52 No. 1 (2024): January-March 2024 /, Power System Protection and Control, ISSN-1674-3415https://pspac.info/index.php/dlbh/article/view/182, DOI: https://doi.org/10.46121/pspc.52.1.3
27. Generative AI for Automated CAD Model Generation in Aerospace Manufacturing, Jawaharbabu Jeyaraman, Feroskhan Hasenkhan, Swetha Ravipudi 9/24/2024, Los

Angeles Journal of Intelligent Systems and Pattern Recognitio, https://lajispr.org/index.php/publication/article/view/19

28. Cloud-Native Architectures for Aerospace: Enhancing Flight Operations Through Digital Airline Platforms, Feroskhan Hasenkhan, Gnanendra Reddy Muthirevula, Sasanian Bhattacharyya, 3/31/2024,American Journal of Autonomous Systems and Robotics Engineering 4, https://ajasre.org/index.php/publication/article/view/25
29. Multi-Cloud Architecture for High-Availability Asset Management Systems Swetha Ravipudi, Feroskhan Hasenkhan, Ravi Kumar Burila12/19/2023 American Journal of Data Science and Artificial Intelligence Innovations 3, https://www.ajdsai.org/index.php/publication/article/view/21
30. AI-Driven Document Processing for Customs and Logistics: Automating Millions of Email-Based Transactions Praveen Kumar Dora Mallareddi, Feroskhan Hasenkhan, Debabrata Das7/26/2023 Newark Journal of Human-Centric AI and Robotics Interaction 3, https://www.njhcair.org/index.php/publication/article/view/13
31. M Niloy, MT Islam, MS Ullah, J Alom, M Ahmed, MF Mridha, MJ Hossen, Lead-Aware Multi-Resolution Transformer With Domain Adaptation for Beat-Level ECG Arrhythmia Classification, Vol. 6 (2025), IEEE Open Journal of the Computer Society, ISSN: 2644-1268, https://ieeexplore.ieee.org/abstract/document/11270234
DOI: https://doi.org/10.1109/OJCS.2025.3637851
32. J Alom, MS Ullah, MDT Islam, M Niloy, R Islam, S Firdaus, Adaptive Multi-Agent Reinforcement Learning for Intrusion Mitigation Aligned with Smart City, 2025 International Conference on Quantum Photonics, Artificial Intelligence and Networking (QPAIN), IEEE, https://ieeexplore.ieee.org/abstract/document/11172093,
DOI: https://doi.org/10.1109/QPAIN66474.2025.11172093
33. J Alom, MS Ullah, MDT Islam, M Niloy, R Islam, S Firdaus, FedGAT-ID: Federated Graph Attention Network with Client Drift-Aware Aggregation for Distributed Cyber Threat Detection, 2025 International Conference on Quantum Photonics, Artificial Intelligence and Networking (QPAIN), IEEE, https://ieeexplore.ieee.org/abstract/document/11172169,
DOI: https://doi.org/10.1109/QPAIN66474.2025.11172169
34. M Niloy, MT Islam, MS Ullah, J Alom, SR Sultana, K Nur, GraphFact-Summ: Graph-Augmented Factual Summarization of Hospital Courses from Clinical Notes, 2025 3rd International Conference on Artificial Intelligence, Blockchain and Internet of Things (AIBThings), IEEE, https://ieeexplore.ieee.org/abstract/document/11296232,
DOI: https://doi.org/10.1109/AIBThings66987.2025.11296232
35. MT Islam, J Alom, M Niloy, MS Ullah, SR Sultana, K Nur, A Heat-Wave-Aware Degree-Day Model for Predicting Flowering Time in Chickpea, 2025 3rd International Conference on Artificial Intelligence, Blockchain and Internet of Things (AIBThings), IEEE, https://ieeexplore.ieee.org/abstract/document/11296213,
DOI: https://doi.org/10.1109/AIBThings66987.2025.11296213
36. Nasik, Basith, and Shanna Nifoussi. "A Comparative Study of MBTI and Learning Style-Based Grouping for Enhancing Group Effectiveness and Balance in a Pedagogical Setting."
[26/05, 05:29] 3- USA Basith: https://osf.io/preprints/edarxiv/h3dea_v1

37. Manikantha Varaprasad Inakollu, (2024, May), FINOPS-Driven Cloud optimization models for enterprise applications, Vol. 52 No. 2 (2024): April-June 2024, 99-110, Power System Protection and Control, ISSN-1674-3415,
URL: https://pspac.info/index.php/dlbh/article/view/283
DOI: https://doi.org/10.46121/pspc.52.2.10
38. Ramchandra Pudasaini. "EVALUATION OF ANTIEPILEPTIC ACTIVITY OF CASSIA AURICULATA FLOWER EXTRACTS IN MICE". Journal of Population Therapeutics and Clinical Pharmacology, vol. 32, no. 3, Apr. 2025, pp. 533-4, https://doi.org/10.53555/8n0prv27.
39. Reserve Bank of India, Monetary Policy Committee: Framework, Functioning, and Forward Guidance, RBI Bulletin, October 2023, pp. 1–24.
40. Government of India, RBI Act 1934 (Amendment 2016): Monetary Policy Committee and Inflation Targeting Framework, Ministry of Finance, 2016.
41. B.S. Bernanke, K.N. Kuttner, What explains the stock market's reaction to Federal Reserve policy? J. Finance 60 (3) (2005) 1221–1257.
42. R. Rigobon, B. Sack, The effects of war risk on U.S. financial markets, J. Banking Finance 29 (7) (2005) 1769–1789.
43. W.B. English, S.J. Van den Heuvel, E. Zakrajsek, Interest rate risk and bank equity valuations, J. Monet. Econ. 80 (2016) 48–65.
44. J. Guo, C. Su, C. Ju, Federal reserve policy announcements and bank stock returns, J. Financ. Econ. 41 (2) (2022) 211–239.
45. T. Lucca, F. Moench, The pre-FOMC announcement drift, J. Finance 70 (1) (2015) 329–371.