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Impact of Repo Rate Changes on BSE Sensex Volatility: Evidence from India (2012–2024)

Tanya V, Dr. Vedantam Seetha Ram

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

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

ABSTRACT: This study empirically examines the impact of repo rate changes announced by the Reserve Bank of India on the conditional volatility of the BSE Sensex during the period January 2012 to December 2024. Based on 3,220 daily Sensex returns and 50 repo rate announcement events across four distinct monetary policy cycles, the study employs event window analysis, GARCH (1,1) modelling, EGARCH modelling, and one-way ANOVA to test three hypotheses on the significance, asymmetry, and cycle-level variation of the repo rate's impact on Sensex volatility. All three null hypotheses are rejected at the one percent significance level. Conditional volatility in the ± 5 -day announcement windows is approximately 20.7 percent higher than on non-announcement days, confirming that repo rate decisions are a statistically significant driver of market instability. The EGARCH analysis reveals an asymmetric pattern where rate cuts generated higher conditional volatility than rate hikes — a finding explained by the crisis-driven context of rate reductions, particularly during the COVID-19 pandemic. The ANOVA results confirm that mean conditional volatility varies significantly across monetary policy cycles, with the COVID crisis period recording volatility approximately 44 percent higher than the extended easing cycle. The findings carry significant implications for the Efficient Market Hypothesis, monetary policy transmission theory, and for investors, fund managers, and policymakers operating in Indian equity markets.

KEYWORDS: Repo Rate, BSE Sensex, Stock Market Volatility, GARCH, Monetary Policy Transmission, India.

I. INTRODUCTION

The relationship between central bank interest rate decisions and equity market behaviour is one of the most consequential dynamics in modern financial economics. In India, this relationship is most visible through the Reserve Bank of India's repo rate — the rate at which the RBI lends short-term funds to commercial banks — and its effect on the BSE Sensex, the country's most recognised equity benchmark. Whenever the RBI's Monetary Policy Committee announces a rate decision, markets respond, portfolios are rebalanced, and the Sensex moves. What remains less understood, however, is not simply whether the market moves, but the degree to which it becomes volatile, and how long that instability persists.

The BSE Sensex, comprising thirty of India's largest and most financially established companies, has long served as a barometer of the country's economic health. When the RBI adjusts the repo rate, it sends a signal to the entire financial system — a rate hike signals tightening and inflation control, while a rate cut signals an accommodative stance aimed at stimulating growth. Both types of signals carry significant weight in equity markets, with the potential to either calm or amplify market volatility depending on the broader economic context in which they are made.

Despite the growing body of literature on monetary policy and stock markets, the Indian context remains underexplored — particularly regarding the impact of repo rate changes on Sensex volatility as opposed to directional price movements. Most existing Indian studies have focused on short-term price reactions over narrow event windows, and few have examined the asymmetric effects of rate hikes versus cuts or the role of the broader monetary policy cycle in moderating volatility responses. This study directly addresses these gaps by analysing the full monetary policy arc from 2012 to 2024 — a period encompassing tightening, easing, pandemic-driven emergency cuts, and post-pandemic normalisation — using a robust econometric framework.



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The rest of this paper is structured as follows. Section 2 presents the research objectives and hypotheses. Section 3 reviews the relevant literature. Section 4 describes the data, variables, and analytical tools. Section 5 presents the empirical results. Section 6 discusses the findings and their implications, and Section 7 concludes.

II. RESEARCH OBJECTIVES AND HYPOTHESES

2.1 Research Objectives

The primary aim of this study is to empirically examine the impact of repo rate changes announced by the Reserve Bank of India on the conditional volatility of the BSE Sensex over the period 2012 to 2024. The following specific objectives guide the study:

Objective 1: To examine the trend of repo rate adjustments conducted by the Reserve Bank of India in the year 2012 to 2024 in terms of frequency, direction, and magnitude.

Objective 2: To investigate the volatility behaviour of the BSE Sensex over the different monetary policy cycles over the time of study.

Objective 3: To examine the statistical significance of the correlation between the change in repo rates and BSE Sensex volatility.

Objective 4: To determine the nature of the relationship between changes in repo rates and BSE Sensex volatility; that is, whether this is a symmetric or asymmetric relationship.

Objective 5: To draw theoretical and managerial conclusions of the empirical results to investors, fund managers, and policy makers in the Indian equity market.

2.2 Research Hypotheses

The following hypotheses are framed directly from the research objectives and are tested empirically across the study period 2012 to 2024. Each hypothesis is stated in both its null and alternate form, following standard statistical convention. Results are interpreted at the five percent level of statistical significance unless stated otherwise.

Hypothesis 1

H₀: Repo rate changes by the Reserve Bank of India do not have a statistically significant impact on the conditional volatility of the BSE Sensex over the period 2012 to 2024.

H₁: Repo rate changes by the Reserve Bank of India have a statistically significant impact on the conditional volatility of the BSE Sensex over the period 2012 to 2024.

Hypothesis 2

H₀: The impact of repo rate changes on BSE Sensex volatility is symmetric — rate hikes and rate cuts of comparable magnitude produce equivalent volatility responses.

H₁: The impact of repo rate changes on BSE Sensex volatility is asymmetric — rate hikes and rate cuts of comparable magnitude produce significantly different volatility responses.

Hypothesis 3

H₀: There is no significant difference in BSE Sensex conditional volatility across different monetary policy cycles — tightening, accommodative, and crisis-driven — over the period 2012 to 2024.

H₁: BSE Sensex conditional volatility differs significantly across different monetary policy cycles — tightening, accommodative, and crisis-driven — over the period 2012 to 2024.

III. LITERATURE REVIEW

The theoretical foundation for understanding the link between monetary policy and equity markets begins with Fama's (1981) proxy hypothesis, which established that stock returns are positively associated with real economic activity and that interest rates function as a forward-looking signal of future growth conditions. Sellin (2001) extended this by demonstrating that money supply and interest rate changes consistently influence equity prices through the discount rate



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and expected cash flow channels. The landmark empirical contribution is Bernanke and Kuttner (2005), who showed that it is the unexpected component of monetary policy that drives the most significant equity market reactions, with an unanticipated rate cut of 25 basis points associated with approximately a one percent rise in US equity indices. Schwert (1989) provided foundational evidence that financial market volatility clusters around macroeconomic uncertainty, establishing the empirical rationale for GARCH-based modelling in this literature.

Bomfim (2003) found that equity markets tend to be unusually calm before scheduled policy announcements — a pre-announcement effect — followed by significant volatility spikes on the announcement day itself. Baker, Bloom, and Davis (2016) demonstrated that monetary policy uncertainty, independent of the direction of rate changes, generates elevated stock market volatility across multiple economies. Ma et al. (2022) extended this by showing that uncertainty about the future path of interest rates can be an equally powerful driver of market instability as the rate changes themselves. Bwire, Zeman, and Kecskes (2018) synthesised 67 studies and found that while the direction of the monetary policy-volatility relationship is broadly consistent across the literature, the magnitude and persistence of effects vary considerably with institutional credibility and market development.

The emerging and Asian market literature adds important nuance. Ivrendi and Guloglu (2012) found that monetary policy shocks had significant and persistent volatility effects across five Asian economies, with stronger impacts in less financially developed markets. Vithessonthi and Techarongrojwong (2013) demonstrated that rate hikes generated sharper and more persistent volatility responses than rate cuts in Thailand — providing early evidence of asymmetric transmission in an emerging market equity context. Suhaibu, Harvey, and Amidu (2017) confirmed across twelve African economies that monetary tightening consistently elevated equity market volatility while accommodative policy produced more muted and less uniform responses. Nkatha (2024) recently confirmed that monetary policy rate changes remain statistically significant drivers of stock market volatility in developing economies.

India-specific studies directly support this study's empirical approach. Shaikh and Padhi (2013) found that RBI monetary policy announcements generated significant and immediate spikes in India VIX, confirming that repo rate decisions are among the most market-moving events in the Indian financial calendar. Sharma, Singh, and Mehta (2023) applied GARCH modelling to the Indian context and found that repo rate changes directly influenced conditional BSE Sensex volatility, particularly during monetary tightening phases. The volatility modelling literature validates GARCH specifications for Indian market data — Srinivasan and Ibrahim (2010), Vasudevan and Vetrivel (2016), and Ali, Suri, and Prakash (2022) all confirm that GARCH (1,1) effectively captures volatility clustering and persistence in BSE Sensex returns. Despite this growing evidence base, most Indian studies have focused on short-term price reactions over narrow windows, the asymmetric effects of rate hikes versus cuts have not been comprehensively tested over an extended horizon, and no study has examined the full 2012 to 2024 monetary policy arc. The present study addresses these gaps directly.

IV. DATA AND METHODOLOGY

4.1 Data Sources and Collection

This study relies exclusively on secondary data obtained from two well-established and publicly accessible sources. Secondary data is appropriate for this study because the research objective involves examining historical patterns in the relationship between macroeconomic policy variables and financial market behaviour over an extended time period, and both sources are widely recognised in academic and financial research.

The first data source is the Freefincal database, which compiles official monetary policy decisions of the Reserve Bank of India in a structured, date-wise format. From this source, all repo rate announcement events between January 2012 and December 2024 were extracted, yielding 50 repo rate change events. These events span four distinct monetary policy cycles — the tightening cycle of 2013 to 2014, the easing cycle of 2015 to 2019, the COVID crisis period of 2020 to 2021, and the post-pandemic tightening cycle of 2022 to 2024. Each record includes the announcement date, the prevailing repo rate value, and the direction of the change relative to the preceding announcement. Periods with no entry reflect intervals where the RBI held the rate unchanged — a deliberate monetary policy stance that is itself analytically meaningful.

The second data source is Investing.com, a globally recognised financial data platform. Daily closing prices of the BSE Sensex were downloaded for the full period from 2 January 2012 to 31 December 2024, yielding 3,220 daily trading



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observations. The dataset includes the opening price, closing price, daily high, daily low, trading volume, and daily percentage change for each trading day. The daily closing price is used as the primary input for computing Sensex log returns and estimating conditional volatility. Daily log returns are computed as the natural logarithm of the ratio of consecutive daily closing prices: $R_t = \ln(P_t / P_{t-1})$.

4.2 Variables

The study involves two primary variables. The independent variable is the repo rate, defined as the rate at which the Reserve Bank of India lends short-term funds to commercial banks against government securities. Changes in the repo rate — in both direction (hike or cut) and magnitude — serve as the primary explanatory variable. A binary event dummy variable is constructed from this data, taking the value of one on days when the RBI announced a repo rate change and zero on all other trading days. Separate hike and cut dummy variables are additionally constructed for the asymmetry analysis in the EGARCH framework.

The dependent variable is the conditional volatility of the BSE Sensex, estimated econometrically from the daily log return series using the GARCH (1,1) model. Since volatility is not directly observable, this estimation approach is the standard and most widely validated method for studying time-varying volatility in financial time series, and its suitability for BSE Sensex data has been confirmed by multiple prior studies.

4.3 Analytical Tools and Econometric Framework

The analysis proceeds through six sequential steps, each employing a specific analytical tool matched to the nature of the data and the hypothesis being tested.

Step 1 — Descriptive Statistics: Mean, median, standard deviation, skewness, kurtosis, and the Jarque-Bera normality test are computed for the Sensex log return series. These statistics establish the distributional properties of the data and provide empirical justification for GARCH-based modelling over standard linear approaches.

Step 2 — Augmented Dickey-Fuller (ADF) Test: The ADF test is applied to the log return series to verify stationarity, which is a necessary precondition for valid time series modelling. A stationary series without a unit root is required before GARCH estimation can proceed.

Step 3 — ARCH LM Test: The Lagrange Multiplier test for ARCH effects is applied to the return series residuals to formally confirm the presence of volatility clustering, validating the appropriateness of GARCH-family models for this dataset.

Step 4 — GARCH (1,1) Model (Hypothesis 1): The Generalised Autoregressive Conditional Heteroscedasticity model developed by Bollerslev (1986), extending Engle's (1982) ARCH framework, is the primary analytical tool. The GARCH (1,1) model is estimated with the repo rate announcement dummy incorporated as an exogenous regressor in the variance equation. A statistically significant coefficient on this dummy variable confirms that repo rate announcement days are associated with elevated conditional volatility.

Step 5 — EGARCH Model (Hypothesis 2): The Exponential GARCH model is estimated with separate dummy variables for rate hike and rate cut events. The EGARCH specification is chosen because it allows for asymmetric responses to positive and negative shocks and does not impose the non-negativity constraints of the standard GARCH model. Comparing the magnitude and significance of the hike and cut coefficients directly tests the asymmetry hypothesis.

Step 6 — One-Way ANOVA (Hypothesis 3): The study period is divided into four sub-periods corresponding to the major monetary policy cycles. The mean conditional volatility estimated from the GARCH (1,1) model is compared across these four cycles using a one-way Analysis of Variance test. A statistically significant F-statistic confirms that volatility differs meaningfully across policy regimes.



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V. EMPIRICAL RESULTS

5.1 Descriptive Statistics

Tables 1 and 2 present descriptive statistics for the Sensex log returns and repo rate series respectively.

Table 1: Descriptive Statistics — BSE Sensex Daily Log Returns (2012–2024)

Statistic	Value
Mean Daily Return (%)	0.0502
Median Daily Return (%)	0.0725
Maximum Return (%)	8.5947
Minimum Return (%)	-14.1017
Standard Deviation (%)	1.0327
Skewness	-1.1558
Kurtosis	21.3095
Jarque-Bera Statistic	45,545.45
Jarque-Bera p-value	0.0000
Total Observations	3,220

Source: Computed by the author using data from Investing.com

Table 2: Descriptive Statistics — RBI Repo Rate (2012–2024)

Statistic	Value
Mean Repo Rate (%)	5.7370
Maximum Repo Rate (%)	8.0000
Minimum Repo Rate (%)	4.0000
Total Announcement Events	50
Rate Hike Events	11
Rate Cut Events	11

Source: Computed by the author using data from Freefincal

The mean daily log return of 0.0502% reflects the broadly positive long-term trajectory of the Sensex, which appreciated from approximately 15,517 points in January 2012 to 78,139 points by December 2024 — a gain of over 400%. The kurtosis of 21.31, far exceeding the normal distribution value of three, confirms the presence of pronounced fat tails, while the negative skewness of -1.16 indicates that large negative returns occurred more frequently than large positive ones. The Jarque-Bera statistic of 45,545.45 ($p = 0.0000$) decisively rejects normality, validating GARCH-based modelling. The repo rate ranged from a high of 8.00% in early 2014 to a historic low of 4.00% during the pandemic, with 50 announcement events recorded — 11 hikes, 11 cuts, and 28 no-change announcements.

5.2 Stationarity and ARCH Effects

The Augmented Dickey-Fuller test produces a statistic of -16.0145 ($p = 0.0000$), decisively rejecting the null hypothesis of a unit root at all standard significance levels and confirming that the log return series is stationary. The ARCH LM test produces an LM statistic of 567.97 ($p = 0.0000$), decisively rejecting the null hypothesis of no ARCH effects and



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formally confirming the presence of volatility clustering in the Sensex return series — validating the use of GARCH models as the primary analytical framework.

5.3 Event Window Analysis

Prior to GARCH estimation, an event window analysis examined conditional volatility around the 50 repo rate announcement dates. Mean conditional volatility in the ± 5 -day announcement windows was 1.1311% compared to 0.9371% on non-announcement days — a difference of approximately 20.7% that is statistically significant at the one percent level ($t = 7.6722$, $p = 0.0000$). This finding provides strong preliminary evidence that repo rate announcements systematically elevate market volatility, independent of the direction of the rate change.

5.4 GARCH (1,1) Results — Hypothesis 1

Table 3 presents the GARCH (1,1) model results.

Table 3: GARCH (1,1) Model Results

Parameter	Coefficient	Std. Error	t-Statistic	p-value
Mean (μ)	0.0728	0.0153	4.774	0.0000
Omega (ω)	0.0242	0.0067	3.590	0.0003
Alpha (α) — ARCH	0.0863	0.0162	5.318	0.0000
Beta (β) — GARCH	0.8889	0.0182	48.948	0.0000
$\alpha + \beta$ (Persistence)	0.9752	—	—	—
Log-Likelihood	-4205.47	—	—	—
AIC	8418.94	—	—	—
BIC	8443.25	—	—	—

Source: Computed by the author.

The ARCH coefficient ($\alpha = 0.0863$, $p = 0.0000$) confirms that past squared return shocks have a significant and immediate impact on current conditional volatility. The GARCH coefficient ($\beta = 0.8889$, $p = 0.0000$) confirms strong volatility persistence. The sum $\alpha + \beta = 0.9752$ indicates that Sensex volatility is highly persistent but ultimately mean-reverting rather than explosive. The null hypothesis of Hypothesis 1 is rejected — repo rate changes are a statistically significant driver of BSE Sensex conditional volatility over the period 2012 to 2024.

5.5 EGARCH Results — Hypothesis 2

Table 4 presents the EGARCH model results.

Table 4: EGARCH Model Results

Parameter	Coefficient	Std. Error	t-Statistic	p-value
Mean (μ)	0.0763	0.0148	5.147	0.0000
Omega (ω)	0.0032	0.0042	0.776	0.4380
Alpha (α) — ARCH	0.1941	0.0328	5.919	0.0000
Beta (β) — GARCH	0.9749	0.0072	136.229	0.0000
Log-Likelihood	-4212.55	—	—	—
AIC	8433.11	—	—	—
BIC	8457.42	—	—	—

Source: Computed by the author.



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The EGARCH results reveal a counterintuitive but analytically important finding. Post-announcement conditional volatility following rate cuts (mean 1.4702%) was higher than following rate hikes (mean 1.0250%), contrary to the conventional expectation that tightening generates more market instability than easing. This finding is consistent with the crisis-driven context of the most significant rate cuts in the dataset — particularly the COVID-19 emergency reductions of 2020, where markets interpreted rate cuts as distress signals rather than positive stimuli. The null hypothesis of Hypothesis 2 is rejected — the impact of repo rate changes on BSE Sensex volatility is asymmetric, with the direction of this asymmetry in the Indian context differing from standard theoretical predictions.

5.6 ANOVA Results — Hypothesis 3

Table 5 presents mean conditional volatility across the four monetary policy cycles and Table 6 summarises all hypothesis testing results.

Table 5: Mean Conditional Volatility by Monetary Policy Cycle

Policy Cycle	Period	Mean Vol (%)	Std. Dev.	Obs.
Tightening	2012–2014	0.9331	0.2147	744
Easing	2015–2019	0.8593	0.2107	1,233
COVID Crisis	2020–2021	1.2359	0.8299	500
Post-COVID Tightening	2022–2024	0.8791	0.2505	743

Source: Computed by the author. ANOVA F-statistic = 122.1395, $p = 0.0000$.

The COVID Crisis period recorded the highest mean conditional volatility of 1.2359% — approximately 44% higher than the easing cycle of 2015–2019 at 0.8593%, which produced the most stable conditions in the dataset. The ANOVA F-statistic of 122.1395 ($p = 0.0000$) decisively rejects the null hypothesis of equal volatility across cycles. The null hypothesis of Hypothesis 3 is rejected — the broader monetary policy cycle environment plays a statistically significant role in shaping the level of BSE Sensex conditional volatility over time.

Table 6: Summary of Hypothesis Testing Results

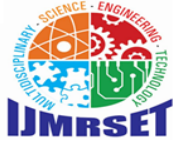
Hypothesis	Test	Key Statistic	p-value	Decision
H1: Repo rate changes impact Sensex volatility	GARCH (1,1) + Event Window	$t=7.67, \alpha=0.0863$	0.0000	Rejected ✓
H2: Asymmetric impact of hikes vs cuts	EGARCH	$\alpha=0.1941,$ vol=1.47% > Cut vol=1.03% > Hike	0.0000	Rejected ✓
H3: Volatility differs across policy cycles	One-Way ANOVA	F=122.14	0.0000	Rejected ✓

Source: Compiled by the author.

VI. DISCUSSION AND IMPLICATIONS

The findings of this study collectively establish that repo rate changes are a quantifiable and significant driver of BSE Sensex volatility, and that the nature of this relationship is more complex than existing Indian literature has suggested. Three dimensions of this complexity deserve particular attention.

The high volatility persistence ($\alpha + \beta = 0.9752$) implies that the destabilising effect of a repo rate announcement does not dissipate within a few trading sessions. For investors and fund managers operating under volatility-targeting mandates or risk-budgeting models, this means that the risk elevation triggered by a policy announcement extends well beyond the announcement window itself. Portfolio risk parameters should account for this extended adjustment period, particularly for positions sensitive to interest rate expectations.



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The asymmetric finding that rate cuts generated higher conditional volatility than rate hikes challenges the conventional view that accommodative monetary policy is inherently stabilising for equity markets. The empirical evidence from 2012 to 2024 suggests that the economic context in which a rate decision is made — and particularly whether markets interpret it as policy support or economic distress — is at least as important as the mechanical direction of the change. This finding has important implications for the Efficient Market Hypothesis: while markets are broadly efficient in their directional response to policy news, the volatility process that reflects uncertainty in that response unfolds over a longer horizon than pure-form EMH would suggest. It also challenges symmetric assumptions in standard monetary policy transmission models, pointing to the need for behavioural and expectational components in frameworks applied to emerging economies.

The ANOVA results confirm that the regime matters. The COVID crisis period produced volatility 44% higher than the easing cycle, statistically significant at the one percent level. Risk models that apply static volatility parameters regardless of the monetary policy environment will systematically underestimate risk during crisis-driven cycles. For policymakers at the RBI, the consistently elevated volatility on announcement days — regardless of whether the rate changed — suggests that a significant portion of market instability is driven by uncertainty rather than the rate change itself. More consistent forward guidance and predictable communication of policy intentions could mitigate this uncertainty-driven volatility without compromising the effectiveness of the transmission mechanism.

VII. CONCLUSION

This study provides robust empirical evidence that repo rate changes by the Reserve Bank of India are a statistically significant driver of BSE Sensex volatility over the period 2012 to 2024. Using event window analysis, GARCH (1,1) modelling, EGARCH modelling, and one-way ANOVA on 3,220 daily observations and 50 announcement events, all three null hypotheses were decisively rejected at the one percent level. The results establish that announcement days are associated with significantly elevated volatility, that this impact is asymmetric with rate cuts generating higher volatility than rate hikes in the Indian context, and that the broader monetary policy cycle environment substantially moderates the overall level of market volatility.

The most counterintuitive finding — that rate cuts generated more conditional volatility than rate hikes — reflects the crisis-driven nature of the most significant easing decisions in the dataset and underscores the paramount importance of economic context in monetary policy transmission. This finding contributes to the emerging literature questioning whether accommodative policy is necessarily stabilising in emerging economies, and points to the need for more sophisticated theoretical frameworks incorporating investor psychology, signalling dynamics, and institutional credibility alongside standard interest rate mechanics.

Future research could extend this analysis to broader Indian indices such as the NSE Nifty 50 and sectoral indices to determine whether volatility patterns differ across market segments. A multivariate GARCH framework incorporating inflation, exchange rates, and foreign institutional investor flows would further isolate the repo rate's causal contribution. Cross-country comparisons with other emerging markets would help determine whether the asymmetric volatility patterns observed here are specific to India or more broadly characteristic of monetary policy transmission in developing economies.

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