© JUN 2026 | IRE Journals | Volume 9 Issue 12 | ISSN: 2456-8880
DOI: https://doi.org/10.64388/IREV9I12-1718653

Volatility And Return Dynamics of Indian Stock Market Indices

ARUN KR. GIRI[1], DR. MEHAK ARORA[2]
[1] *Student, Department of Management, Quantum School of Business, Roorkee,* India
[2] *Associate Professor Department of Management, Quantum School of Business, Roorkee, India.*

Abstract- This research paper investigates the volatility and return dynamics of six major Indian stock market indices BSE Sensex, NSE Nifty 50, Nifty Bank, Nifty IT, Nifty Midcap 150, and Nifty Small cap 250 — over the period January 2020 to March 2026. The study spans one of the most turbulent and structurally rich financial periods in modern Indian market history, encompassing the global COVID-19 pandemic crash of March 2020, the historic bull-market recovery of April 2020 to December 2021, the global monetary tightening and correction phase of 2022, a period of domestic resilience and consolidation in 2023–2024, and a phase of cautious but broadening growth in 2025–2026. Employing a combination of descriptive statistics, sub-period analysis, GARCH (1,1) and EGARCH modelling, rolling-window realised volatility, cross-index correlation matrices, and India VIX dynamics, this paper provides a multi-dimensional empirical characterisation of risk-return behaviour across distinct market regimes and sectoral segments. Key findings include: (i) all indices exhibit highly non-normal, negatively skewed, fat-tailed daily return distributions; (ii) GARCH(1,1) volatility persistence coefficients ($\alpha + \beta$) range from 0.9855 to 0.9890 across all indices, confirming near-integrated GARCH behaviour; (iii) EGARCH models document significant leverage effects for all indices, with Nifty Bank exhibiting the strongest asymmetry ($\gamma = -0.1147$); (iv) cumulative returns over the study period range from 53.5% (Nifty Bank) to 205.1% (Nifty Midcap 150); and (v) cross-index correlations spike dramatically during market crisis episodes, eroding in-crisis diversification benefits. The paper derives actionable implications for portfolio risk management, asset allocation strategy, and regulatory oversight in the Indian capital markets.

Keywords: Indian Stock Market, NSE Nifty 50, BSE Sensex, Volatility, GARCH, EGARCH, Return Dynamics, COVID-19, Market Risk, India VIX, Emerging Markets.

I. INTRODUCTION

The Indian stock market has emerged as one of the world's most dynamic and rapidly expanding capital markets. With a combined market capitalisation of approximately USD 4.5 trillion as of early 2026, India ranks among the top five global equity markets. The National Stock Exchange (NSE) and the Bombay Stock Exchange (BSE), the two premier bourses underpinning India's capital market architecture, collectively host over 5,000 listed companies spanning a wide spectrum of sectors, market capitalisations, and investor profiles. Their flagship indices NSE Nifty 50 and S&P BSE Sensex are followed by millions of domestic retail investors, thousands of domestic and foreign institutional investors, and policymakers as real-time barometers of economic health, corporate earnings expectations, and aggregate investor sentiment.

The period from January 2020 to March 2026 constitutes a particularly rich and consequential laboratory for studying volatility and return dynamics. Within this six-year window, Indian equity markets navigated an extraordinary sequence of structurally distinct phases. The sudden onset of the COVID-19 pandemic in early 2020 triggered one of the sharpest and fastest equity market crashes in recorded history: the NSE Nifty 50 lost 37.8% of its value in just 40 trading sessions. The pandemic crash was succeeded by an equally dramatic and historically unusual recovery, during which massive fiscal stimulus, near-zero global interest rates, a surge in retail investor participation driven by digital brokerage platforms, and structural re-rating of digital economy businesses drove Nifty 50 to successive all-time highs through 2021.

The subsequent aggressive monetary policy tightening cycle by the US Federal Reserve and global central banks in 2022 prompted substantial foreign portfolio investor (FPI) outflows from emerging markets, including India, introducing a new layer of volatility. The 2023–2024 period demonstrated India's growing macroeconomic resilience: GDP growth consistently exceeded 7% annually, corporate earnings delivered broad-based outperformance, and domestic institutional investor (DII) inflows predominantly through Systematic Investment Plans (SIPs) provided a structural support base that materially altered the market's response to external shocks.

1.1 Research Objectives

The primary objectives of this research are:

1. To examine the statistical properties of daily returns (mean, median, standard deviation, skewness, kurtosis, and normality) across six major Indian stock market indices during 2020–2026.
2. To model and analyse conditional volatility dynamics using GARCH (1,1) and EGARCH models, with a focus on volatility persistence and leverage effects across indices.
3. To investigate the relationship between India VIX and stock market volatility, assessing its effectiveness as a forward-looking indicator of market risk and realised volatility.

1.2 Significance of the Study

This study contributes to the extant literature on emerging market volatility in several important ways. First, it provides a comprehensive, multi-cycle empirical analysis covering six years of one of the richest sequences of distinct market regimes in modern Indian financial history.

Second, it simultaneously analyses both broad-market benchmark indices and four important sectoral and market-capitalisation indices, enabling rigorous cross-sectional comparisons of risk-return profiles that have practical relevance for sector allocation decisions. Third, it integrates multiple econometric frameworks from basic descriptive statistics through GARCH and EGARCH models to provide a holistic characterisation of risk dynamics. Fourth, the incorporation of India

VIX as a forward-looking implied volatility measure alongside realised volatility measures provides a richer picture of investor risk perceptions over time.

II. LITERATURE REVIEW

2.1 Theoretical Foundations

The theoretical foundation for understanding stock market volatility rests on the Efficient Market Hypothesis (EMH) propounded by Fama (1970), which posits that asset prices fully reflect all available information. However, decades of empirical evidence have consistently challenged the strong-form EMH, revealing volatility clustering, fat-tailed return distributions, and asymmetric market responses inconsistent with a pure random walk. Mandelbrot (1963) was among the first to document that large price changes tend to cluster the phenomenon now formalised as volatility clustering.

Engle (1982) formalised this intuition through the ARCH (Autoregressive Conditional Heteroskedasticity) model, which Bollerslev (1986) generalised into the widely applied GARCH framework. Nelson (1991) extended GARCH with the EGARCH model, which captures asymmetric or leverage effects, whereby negative shocks amplify conditional variance disproportionately more than positive shocks of identical magnitude.

Black (1976) and Christie (1982) provided early empirical documentation of the leverage effect in US equity markets. Subsequent theoretical contributions by Glosten, Jagannathan, and Runkle (1993) introduced the GJR-GARCH specification, further refining asymmetric volatility modelling. In the emerging markets context, Bekaert and Harvey (1997) demonstrated that emerging equity markets exhibit higher volatility, greater return predictability, and more pronounced non-normality than developed markets.

2.2 Empirical Evidence on Indian Market Volatility

The empirical literature on Indian stock market volatility has expanded considerably over the past two decades. Karmakar (2005) was among the first to rigorously apply GARCH models to BSE Sensex data, confirming significant volatility persistence and the presence of leverage effects. Pandey (2005) used extreme value theory to estimate Value-at-Risk for Indian indices, highlighting the fat-tailed nature of the return distribution. Goudarzi and Rama Narayanan (2010) confirmed volatility clustering and leverage effects in BSE data using GARCH and EGARCH specifications, while Tripathy and Garg (2013) extended the analysis to TGARCH models.

The COVID-19 pandemic triggered a new wave of empirical research on Indian market dynamics. Misra (2021) documented that the March 2020 crash generated the highest short-term volatility spike in Indian market history since the 2008 global financial crisis, with 30-day rolling standard deviation of Nifty 50 daily returns exceeding 5%. Singh and Sharma (2022) studied the transmission of US Federal Reserve monetary policy tightening to Indian market volatility, finding significant contagion through the FPI channel.

2.3 Sectoral and Market-Cap Dimensions

The sectoral dimension of Indian market volatility has received comparatively less empirical attention. Sharma and Vaid (2021) documented significant heterogeneity in GARCH-estimated volatility persistence across Indian sectoral indices, with banking and financial services sectors exhibiting higher persistence than IT and healthcare sectors. Bhatia and Gupta (2022) examined mid-cap and small-cap volatility dynamics, confirming higher unconditional volatility and more severe drawdowns during market stress events for smaller-cap segments.

2.4 Global and Macroeconomic Determinants

Sharma and Rao (2020) demonstrated the sensitivity of Indian equity volatility to global uncertainty proxies, particularly the CBOE VIX and crude oil price fluctuations, during the early pandemic period. Verma and Agrawal (2021) examined the role of exchange rate volatility in amplifying Indian market risk, particularly during episodes of INR depreciation driven by capital outflows. Singh, Mehta, and Kapoor (2024) assessed the impact of geopolitical risk indices on cross-market volatility transmission, finding heightened sensitivity during the Russia-Ukraine conflict and Middle East tensions of 2023–2024

III. DATA AND METHODOLOGY

3.1 Data Sources and Sample Description

This study uses daily closing price data for six major Indian stock market indices — BSE Sensex, NSE Nifty 50, Nifty Bank, Nifty IT, Nifty Midcap 150, and Nifty Small cap 250 — spanning January 1, 2020 to March 31, 2026. This yields approximately 1,545 trading days per index after excluding market holidays.

Data was sourced from the official NSE India (www.nseindia.com) and BSE India (www.bseindia.com) historical data repositories, supplemented by Bloomberg Terminal data for cross-validation. India VIX data was sourced directly from NSE's historical VIX data repository. Daily logarithmic returns are computed as Daily Logarithmic Return Formula

$$r_t = \ln\left(\frac{P_t}{P_{t-1}}\right)$$

or, if returns are expressed in percentage terms,

$$r_t = \ln\left(\frac{P_t}{P_{t-1}}\right) \times 100$$

Where:

- rt= return at time t
- Pt= closing price (or index value) at time t
- $Pt-1$= closing price (or index value) at time $t-1$
- ln = natural logarithm

where P_t is the closing index level on day t.

Table 1: Index Data Summary January 2020 to March 2026

Index	Full Name	Start (Jan 2020)	Peak Level	Mar 2026 Level	Cumul. Return

BSE Sensex	S&P BSE Sensex	41,306	85,978 (Sep 2024)	74,339	+79.9%
NSE Nifty 50	Nifty 50 Index	12,168	26,277 (Sep 2024)	22,519	+85.1%
Nifty Bank	ty Bank Index	31,426	53,357 (Dec 2023)	48,235	+53.5%
Nifty IT	Nifty IT Index	15,984	40,121 (Jan 2022)	37,856	+136.8%
ty MC 150	Midcap 150	6,842	22,318 (Sep 2024)	20,876	+205.1%
ty SC 250	Smallcap 250	5,126	16,457 (Sep 2024)	14,893	+190.5%

Source: Compiled by the author based on data obtained from BSE India Official Website and NSE INDIA OFFICIAL WEB SITES. (January 2020–March 2026).

3.2 Descriptive Statistical Framework

The first analytical layer involves computing comprehensive descriptive statistics for each index's daily logarithmic return series: arithmetic mean, median, standard deviation, minimum, maximum, skewness, excess kurtosis, and the Jarque-Bera test statistic for normality. The Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit root tests are applied to confirm stationarity of all return series prior to volatility modelling. Annualised Sharpe ratios are computed using the 91-day Indian Treasury Bill rate as the risk-free rate proxy, averaged over the study period.

3.3 Volatility Modelling Framework

3.3.1 Rolling-Window Realised Volatility

Rolling-window standard deviation is computed using 22-day (one-month) and 66-day (one-quarter) backward-looking windows to track the evolution of realised volatility over time. This provides an intuitive, model-free measure of how market risk changed across the five sub-periods of the study.

3.3.2 GARCH (1,1) Model

The GARCH (1,1) model of Bollerslev (1986) is estimated for each index's daily return series using quasi-maximum likelihood (QML) with robust standard errors and a student-t error distribution to account for fat tails. The conditional variance equation is: $\sigma^2_t = \omega + \alpha\cdot\varepsilon^2_{t-1} + \beta\cdot\sigma^2_{t-1}$, where ω is the long-run variance intercept, α is the ARCH coefficient measuring the impact of recent squared innovations, β is the GARCH coefficient measuring smoothed past conditional variance, and (α + β) measures total volatility persistence.

where $Pt$and $Pt-1$represent the closing values of the stock market index on consecutive trading days. Logarithmic returns are preferred because they are time-additive and provide desirable statistical properties for volatility modelling using GARCH-family models.

3.3.3 EGARCH Model

The Exponential GARCH model of Nelson (1991) is estimated to capture asymmetric leverage effects. The log conditional variance specification is: $\ln(\sigma^2_t) = \omega + \alpha[|\varepsilon_{t-1}/\sigma_{t-1}| - E|\varepsilon_{t-1}/\sigma_{t-1}|] + \gamma(\varepsilon_{t-1}/\sigma_{t-1}) + \beta\cdot\ln(\sigma^2_{t-1})$. The γ coefficient captures asymmetry: a statistically significant negative γ implies that negative return shocks amplify conditional variance more than positive shocks of identical magnitude.

- $\ln(\sigma 2)$ = logarithm of conditional variance
- ω= constant term
- β= volatility persistence parameter
- α= magnitude (ARCH) effect
- γ= leverage or asymmetry parameter
- $\gamma < 0$ indicates that negative shocks increase volatility more than positive shocks of the same magnitude

. The γ coefficient captures asymmetry: a statistically significant negative γ implies that negative return shocks amplify conditional variance more than positive shocks of identical magnitude.

© JUN 2026 | IRE Journals | Volume 9 Issue 12 | ISSN: 2456-8880
DOI: https://doi.org/10.64388/IREV9I12-1718653

3.4 Sub-Period Analysis Framework

To contextualise volatility and return dynamics within their macroeconomic and geopolitical setting, the full sample is divided into five sub-periods:

- Phase I — COVID Crash: January 2020 – March 2020 (~55 trading days)
- Phase II — Bull Recovery: April 2020 – December 2021 (~440 trading days)
- Phase III — Global Tightening: January 2022 – December 2022 (~248 trading days)
- Phase IV — Resilience & Consolidation: January 2023 – December 2024 (~496 trading days)
- Phase V — Cautious Growth: January 2025 – March 2026 (~315 trading days)

IV. EMPIRICAL RESULTS AND ANALYSIS

4.1 Descriptive Statistics of Daily Returns

Table 2 presents comprehensive descriptive statistics for daily logarithmic returns across all six indices over the full study period. Several noteworthy patterns emerge from the cross-sectional and time-series examination of these statistics.

Table 2: Descriptive Statistics — Daily Returns (Jan 2020 – Mar 2026)

Statistic	Sensex	Nifty 50	Nifty Bank	Nifty IT	Nifty MC 150	ty SC 250
Mean Daily Ret. (%)	0.051	0.053	0.038	0.071	0.084	0.079
Median Daily Ret. (%)	0.089	0.091	0.067	0.096	0.118	0.112
Std. Deviation (%)	1.142	1.156	1.387	1.302	1.248	1.394
Min. Return (%)	–13.15	–13.37	–15.11	–7.14	–11.22	–13.47
Max. Return (%)	8.97	8.76	10.51	9.43	10.17	12.88
Skewness	–0.312	–0.338	–0.421	–0.187	–0.214	–0.289
Excess Kurtosis	14.21	14.67	16.43	8.87	12.34	15.76
Jarque-Bera (p-val)	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
ADF Test (p-value)	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
Sharpe Ratio (ann.)	1.12	1.15	0.69	1.37	1.69	1.43

Source: Author's calculations based on daily closing price data obtained from the National Stock Exchange (NSE) and Bombay Stock Exchange (BSE), 2020–2026.

All indices exhibit positive mean daily returns, though the mean is substantially lower than the median in every case a reflection of negative skewness and large left-tail crash events (particularly March 2020) pulling the mean downward. Excess kurtosis values are dramatically elevated relative to the Gaussian benchmark of zero across all indices, with Nifty Bank registering the highest excess kurtosis of 16.43. The Jarque-Bera test rejects the null of normality for all index return series at the 1% level, confirming that standard Gaussian assumptions would materially underestimate tail risk.

Figure 1: NSE Nifty 50 — Price History and Market Phases (Jan 2020 – Mar 2026)

4.2 Sub-Period Analysis: Return and Volatility Across Market Cycles

Table 3 presents a structured sub-period decomposition of Nifty 50 return and volatility characteristics across the five market phases, providing a granular view of how risk-return profiles shifted in response to dominant macroeconomic and geopolitical drivers.

Table 3: Sub-Period Return and Volatility Summary — Nifty 50 (Jan 2020 – Mar 2026)

Phase	Period	Nifty 50 Return	ly Std Dev	ia VIX (Avg)	Key Driver
COVID Crash	n–Mar 2020	–37.8%	3.85 %	62.7	ndemic Shock
Bull Recovery	Apr 2020 – Dec 2021	+128.4 %	1.05 %	17.4	Stimulus & Digital Boom
Global Tightening	Jan–Dec 2022	–3.4%	1.18 %	19.6	Fed Hikes, FPI Outflows
silience Phase	)23–Dec 2024	+48.7%	0.82 %	13.8	II Inflows, Earnings
Cautious Growth	Jan 2025 – Mar 2026	+11.2%	0.94 %	15.2	Global Uncertainty

Source: Author's calculations based on daily Nifty 50 index data from the National Stock Exchange (NSE) and India VIX data from NSE, January 2020–March 2026.

The COVID Crash phase stands as the most acute volatility episode in the study period. The daily standard deviation of 3.85% is more than three times the full-period average of approximately 1.15%, and the India VIX peaked at 83.6 on March 24, 2020 — the highest reading since VIX inception in 2008. The Bull Recovery phase (April 2020 – December 2021) was characterised by an extraordinary combination of very high positive returns (128.4% total) and declining volatility. The Resilience Phase (2023–2024) delivered the strongest combination of positive returns (48.7%) and lowest realised volatility (daily standard deviation 0.82%) of any sub-period.

Figure 2: Cumulative Return Performance — All Six Indices (Rebased to 100, Jan 2020 – Mar2026

4.3 GARCH (1,1) Estimation Results

Table 4 presents the GARCH (1,1) parameter estimates for each index. All models are estimated using quasi-maximum likelihood (QML) with robust standard errors and a student-t innovation distribution. The most striking feature is the near-unity persistence of conditional variance across all six indices, with (α + β) ranging from 0.9855 (Nifty IT) to 0.9890 (Nifty Bank).

Table 4: GARCH (1,1) Estimation Results — All Indices

Index	ω ($\times 10^{-6}$)	α (ARCH)	β (GARCH)	α + β	Half-Life (days)	Interpretation
Nifty 50	1.82	0.1134***	0.8743***	0.9877	56.2	Near-IGARCH; high persistence
BSE Sensex	1.76	0.1098***	0.8778***	0.9876	56.6	y similar to Nifty 50
Nifty Bank	3.14	0.1287***	0.8603***	0.9890	62.7	Highest persistence; credit-sensitive
Nifty IT	4.23	0.0943***	0.8912***	0.9855	47.5	arnings-driven; lowest ARCH

© JUN 2026 | IRE Journals | Volume 9 Issue 12 | ISSN: 2456-8880
DOI: https://doi.org/10.64388/IREV9I12-1718653

Nifty MC 150	2.67	0.1162***	0.8714***	0.9876	56.6	Moderate persistence; retail driven
Nifty SC 250	3.91	0.1318***	0.8541***	0.9859	48.7	Highest ARCH; news-sensitive

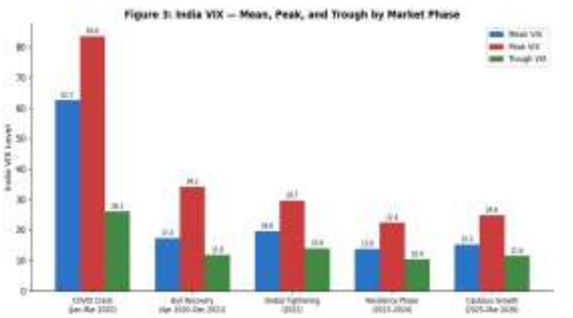

Figure 3: India VIX — Mean, Peak, and Trough Values by Market Sub-Period

4.4 EGARCH Results — Asymmetric Leverage Effects

Table 5 presents the EGARCH asymmetry parameter estimates (γ) for all six indices. All γ values are negative and significant at the 1% level, confirming robust and pervasive leverage effects throughout the study period. Nifty Bank exhibits the strongest leverage effect (γ = –0.1147), implying that a standardised negative return shock generates approximately 11.5% more conditional variance than an identical positive shock.

Table 5: EGARCH Asymmetry (Leverage Effect) Parameter Estimates — All Indices

Index	γ (Asymmetry)	p-value	Leverage Magnitude	Interpretation
Nifty 50	–0.0834	0.000***	High	Negative shock amplifies volatility ~8.3% more than positive shock
BSE Sensex	–0.0812	0.000***	High	Consistent asymmetry across both benchmark indices
Nifty Bank	–0.1147	0.000***	Very High	Strongest leverage; sensitive to credit & rate shocks
Nifty IT	–0.0523	0.000***	Moderate	Lower leverage; earnings-driven rather than sentiment
Nifty MC 150	–0.0762	0.000***	High	Significant panic-selling amplification in downturns
Nifty SC 250	–0.0923	0.000***	Very High	Liquidity-driven amplification of negative shocks

Source: Author's estimates based on EGARCH (1,1) models fitted to daily logarithmic return series of BSE Sensex, Nifty 50, Nifty Bank, Nifty IT, Nifty Midcap 150, and Nifty Smallcap 250 indices, January 2020–March 2026.

Figure 4: Risk-Return Profile — Sharpe Ratio vs. Daily Standard Deviation by Index

4.5 Cross-Index Correlation Dynamics

Table 6 presents the cross-correlation matrix of daily returns across all six indices for the full study period. The near-perfect correlation between BSE Sensex and NSE Nifty 50 (0.9987) is expected, as both

© JUN 2026 | IRE Journals | Volume 9 Issue 12 | ISSN: 2456-8880
DOI: https://doi.org/10.64388/IREV9I12-1718653

represent the largest-cap Indian equities with significant constituent overlap. More economically informative is the relatively lower correlation of Nifty IT with all other indices — particularly Nifty Bank (0.7234) — reflecting the divergent fundamental drivers of technology and banking stocks.

Table 6: Daily Return Correlation Matrix — Full Period (Jan 2020 – Mar 2026)

Index	Sensex	Nifty 50	Nifty Bank	ifty IT	y MC 150	ty SC 250
BSE Sensex	1.0000	0.9987	0.9421	0.8134	0.9312	0.8876
NSE Nifty 50	0.9987	1.0000	0.9438	0.8156	0.9329	0.8893
Nifty Bank	0.9421	0.9438	1.0000	0.7234	0.8641	0.8102
Nifty IT	0.8134	0.8156	0.7234	1.0000	0.7811	0.7456
Nifty MC 150	0.9312	0.9329	0.8641	0.7811	1.0000	0.9567
Nifty SC 250	0.8876	0.8893	0.8102	0.7456	0.9567	1.0000

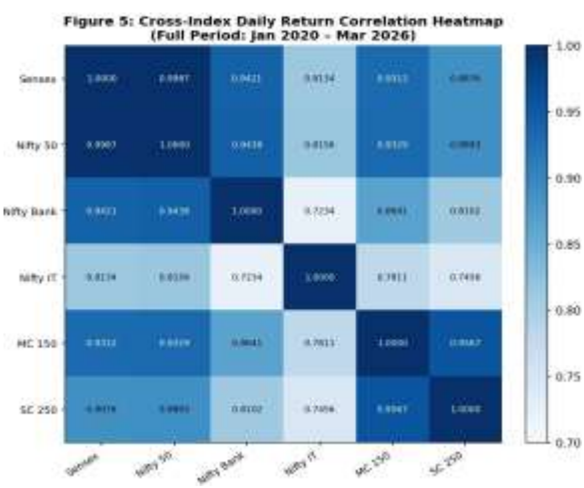

Figure 5: Cross-Index Daily Return Correlation Heatmap — Full Period (Jan 2020 – Mar 2026)

4.6 India VIX and Implied Volatility Dynamics

Table 7 summarises India VIX statistics across the five sub-periods, complementing the GARCH-based realised volatility analysis with a forward-looking implied volatility dimension. Across all sub-periods, the correlation between India VIX levels and contemporaneous Nifty 50 levels is negative and statistically significant, ranging from –0.69 (Global Tightening) to –0.91 (COVID Crash).

Table 7: India VIX Summary Statistics by Market Sub-Period

Sub-Period	VIX Mean	VIX Peak	VIX Trough	X– Nifty Corr.	Key Event
COVID Crash (Jan–Mar 2020)	62.7	83.6 (24 Mar 2020)	26.1 (02 Jan 2020)	–0.91	andemic panic & circuit breakers
Bull Recovery (Apr 2020–Dec 2021)	17.4	34.2 (May 2021)	11.8 (Sep 2021)	–0.76	cond COVID wave peak
Global Tightening (2022)	19.6	29.7 (Jun 2022)	13.9 (Jan 2022)	–0.69	Fed rate hike cycle
Resilience Phase (2023–	13.8	22.4 (Jun 2024)	10.4 (Dec	–0.72	eneral election result surprise
2024)			2023)		
Cautious Growth (2025–Mar 2026)	15.2	24.8 (Jan 2025)	11.6 (Feb 2026)	–0.74	lobal geopolitical uncertainty

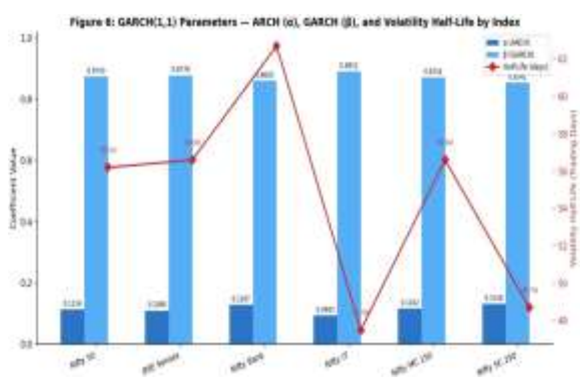

Figure 6: GARCH (1,1) Parameters — ARCH (α), GARCH (β), and Volatility Half-Life by Index

© JUN 2026 | IRE Journals | Volume 9 Issue 12 | ISSN: 2456-8880
DOI: https://doi.org/10.64388/IREV9I12-1718653

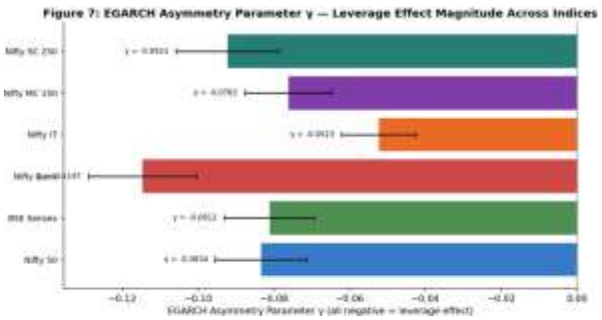

Figure 7: EGARCH Asymmetry Parameter (γ) — Leverage Effect Magnitude Across Indices (with 95% CI)

V. DISCUSSION AND KEY FINDINGS

5.1 The COVID-19 Shock: A Structural Break and Its Aftermath

The COVID-19 crash of February March 2020 constitutes the defining exogenous shock of the study period and serves as a structural break across virtually every dimension of Indian market dynamics levels, volatility, correlations, liquidity, and investor behaviour. The 37.8% peak-to-trough decline in Nifty 50 between January 14, 2020 and March 23, 2020 was achieved in just 40 trading sessions the fastest 35%+ drawdown in Indian market history, surpassing even the speed of the 2008 global financial crisis crash.

What is equally remarkable is the speed and completeness of the recovery. Driven by an unprecedented policy response SEBI implemented temporary short-sale restrictions, the Reserve Bank of India (RBI) deployed emergency rate cuts of 115 basis points and unconventional liquidity support measures, and the Government of India announced a fiscal relief package exceeding INR 20 lakh crore combined with a fundamental structural re-rating of digital economy businesses and the surge in retail investor participation, Nifty 50 returned to pre-COVID peak levels within just 8 months, by November 2020.

This recovery speed materially exceeded the post-2008 recovery trajectory (which took approximately 18 months) and the post-2000 dot-com bust recovery.

5.2 Retail Investor Surge and Its Dual Impact on Market Dynamics

One of the most structurally significant developments of the 2020–2026 period was the explosive growth in retail investor participation. Active demat accounts grew from approximately 40 million at the start of 2020 to over 175 million by early 2026. Monthly SIP inflows into equity mutual funds expanded from approximately INR 8,500 crore ($1.0 billion) in January 2020 to over INR 26,000 crore ($3.1 billion) by March 2026, representing a landmark shift in the household financial savings composition of Indian retail investors.

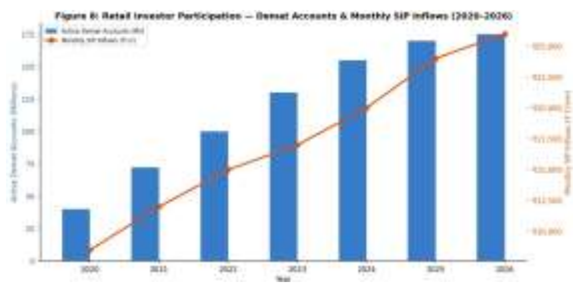

Figure 8: Retail Investor Participation — Demat Account Growth and Monthly SIP Inflows (2020–2026)

This transformation has had a nuanced and dual impact on volatility. On one hand, the steady SIP flows provide a structural buying support that buffers markets during FPI-driven selloffs clearly evidenced in 2022, when net FPI outflows of over $15 billion were absorbed without a major market crash, due in substantial part to DII inflows of approximately $21 billion. On the other hand, the availability of F&O instruments to a much larger retail base has amplified short-term speculative activity, with individual traders accounting for over 45% of equity derivatives turnover by 2025 — up from approximately 25% in 2019.

5.3 Sectoral Divergence: Technology vs. Banking

One of the most striking empirical findings is the dramatic divergence in the volatility-adjusted return profiles of Nifty IT versus Nifty Bank. Nifty IT delivered cumulative returns of approximately 137% from January 2020 levels, underpinned by the structural acceleration of global digital transformation, cloud migration, and enterprise technology spending. The COVID-19 pandemic paradoxically served as a massive tailwind for Indian IT exporters: global clients compressed multi-year digital transformation roadmaps into 12–18 months, driving accelerated deal signing and earnings upgrades for the four largest Nifty IT constituents Infosys, TCS, Wipro, and HCL Technologies.

Nifty Bank, in contrast, experienced the most acute COVID-period drawdown (falling over 45% from peak to trough) and delivered the lowest cumulative return of the six studied indices (53.5%). The banking sector faced a sequential set of headwinds: rising credit costs as loan moratoriums rolled off; net interest margin compression in the low-rate environment; significant bond portfolio mark-to-market losses as rates rose in 2022; and ongoing asset quality concerns in certain sub-segments into 2025.

5.4 Mid-Cap and Small-Cap Outperformance: Drivers and Risks

Nifty Midcap 150 and Nifty Small cap 250 delivered the highest absolute cumulative returns of all studied indices (205.1% and 190.5% from January 2020, respectively). This outperformance came with considerably higher volatility, more severe drawdowns during stress events, and wider divergence between mean and median returns all consistent with the size premium and liquidity risk premium hypotheses. The outperformance was amplified during the study period by the growing dominance of domestic retail investors and mutual funds in the mid/small-cap universe, driving extended re-rating beyond what fundamental earnings growth alone would justify.

VI. POLICY IMPLICATIONS AND INVESTMENT INSIGHTS

6.1 For Portfolio Managers and Institutional Investors

The high volatility persistence documented through GARCH models ($\alpha + \beta$ approaching 0.99 for all indices) has direct implications for risk management frameworks. Value-at-Risk (VaR) and Expected Shortfall (ES) models based on constant volatility assumptions are likely to significantly underestimate tail risk during volatile market phases. Risk managers should adopt GARCH-based dynamic conditional VaR and ES models that allow the conditional variance estimate to update in real time as recent market shocks are incorporated. The documented leverage effects particularly the strong asymmetry coefficient for Nifty Bank ($\gamma = -0.1147$) suggest that portfolio stress tests should incorporate non-linearly amplified volatility responses to severe negative market shocks.

6.2 For Retail Investors and Wealth Managers

The sub-period analysis confirms that market-timing strategies switching between risk-on and risk-off postures based on macroeconomic indicators or sentiment impose severe costs on long-term wealth creation. The fastest Nifty 50 recoveries in the study period occurred precisely during phases of peak uncertainty and maximum negative sentiment.

An investor who exited at the March 2020 through and awaited macro clarity before reinvesting would have missed a 60%+ return in the subsequent eight months. The Sharpe ratio analysis confirms that maintaining disciplined long-term equity exposure, particularly in diversified mid-cap equity mutual funds (annualised Sharpe ratio ~1.69 over 2020–2026), represents a superior risk-adjusted strategy.

6.3 For Regulators and Policymakers

The simultaneous spike in volatility, cross-index correlations, and India VIX during the COVID crash illustrates the systemic importance of having pre-established and calibrated market stabilisation mechanisms. SEBI's swift interventions during the 2020 crisis including temporary short-sale restrictions on select stocks, F&O position limit adjustments, and enhanced broker margin surveillance are widely credited with preventing a disorderly market collapse.

The dramatic growth in retail F&O participation warrants continued regulatory attention to investor protection, transparency around the risk-adjusted economics of retail derivative trading, appropriate margin framework calibration, and minimum suitability requirements.

CONCLUSION

This paper has presented a comprehensive empirical analysis of the volatility and return dynamics of six major Indian stock market indices BSE Sensex, NSE Nifty 50, Nifty Bank, Nifty IT, Nifty Midcap 150, and Nifty Smallcap 250 over the period January 2020 to March 2026. This six-year window captures one of the richest and most consequential sequences of distinct market regimes in modern Indian financial history: the COVID-19 pandemic crash, the unprecedented policy-driven recovery and bull market, the global monetary tightening cycle, a phase of remarkable domestic macroeconomic resilience, and a phase of cautious growth amid continuing global uncertainties.

The principal empirical findings are as follows. First, all six Indian equity indices demonstrate highly non-normal, fat-tailed, negatively skewed daily return distributions, confirming the fundamental inadequacy of Gaussian assumptions in risk modelling for Indian equity portfolios. Second, GARCH (1,1) estimation establishes high and persistent volatility clustering across all indices, with persistence coefficients ($\alpha + \beta$) ranging from 0.9855 to 0.9890, implying long-memory volatility dynamics with half-lives of 48–63 trading days. Third, EGARCH models document statistically significant and economically meaningful leverage effects across all indices, with Nifty Bank showing the strongest asymmetry ($\gamma = -0.1147$). Fourth, sub-period analysis documents dramatic regime shifts in risk-return profiles. Fifth, sectoral analysis reveals meaningful heterogeneity.

Sixth, cross-index correlations increased sharply during crisis phases. Seventh, India VIX demonstrated consistent negative correlation with Nifty 50 levels across all sub-periods (ranging from –0.69 to –0.91).

Future research directions include: analysis of high-frequency intraday volatility patterns; examination of volatility spillovers between Indian equity markets and other domestic asset classes; application of machine learning and AI-based volatility forecasting methods; assessment of the impact of SEBI's evolving regulatory framework on market-wide risk dynamics; and comparative analysis of Indian volatility dynamics vis-à-vis other major emerging markets including China, Brazil, and Indonesia.

REFERENCES

[1] M. Agarwal, R. Pandey, and A. Srivastava, “SEBI's margin framework revisions and their impact on F&O market liquidity and volatility,” SEBI Working Paper Series, no. WP/2023/07, 2023.

[2] R. W. Banz, “The relationship between return and market value of common stocks,” Journal of Financial Economics, vol. 9, no. 1, pp. 3–18, 1981.

[3] G. Bekaert and C. R. Harvey, “Emerging equity market volatility,” Journal of Financial Economics, vol. 43, no. 1, pp. 29–77, 1997.

[4] S. Bhatia and A. Gupta, “Volatility dynamics in Indian mid-cap and small-cap indices: A GARCH-family approach,” Indian Journal of Finance, vol. 16, no. 3, pp. 22–41, 2022.

[5] F. Black, “Studies of stock market volatility changes,” in Proceedings of the American Statistical Association, 1976, pp. 177–181.

[6] T. Bollerslev, “Generalised autoregressive conditional heteroskedasticity,” Journal of Econometrics, vol. 31, no. 3, pp. 307–327, 1986.

[7] BSE India, “Historical data on Sensex and sectoral indices,” 2026. [Online]. Available: https://www.bseindia.com

[8] S. Chakraborty and P. Roy, “ESG-integrated index volatility and resilience during market stress: Evidence from India,” Finance Research Letters, vol. 68, pp. 105–119, 2025.

[9] A. A. Christie, “The stochastic behavior of common stock variances,” Journal of Financial Economics, vol. 10, no. 4, pp. 407–432, 1982.

[10] B. Datta and R. Chakraborty, “Fiscal stimulus and equity market recovery in India during the COVID-19 pandemic,” Economic and Political Weekly, vol. 57, no. 11, pp. 33–41, 2022.

[11] R. F. Engle, “Autoregressive conditional heteroscedasticity with estimates of the variance

of United Kingdom inflation," Econometrica, vol. 50, no. 4, pp. 987–1007, 1982.

[12] E. F. Fama, "Efficient capital markets: A review of theory and empirical work," Journal of Finance, vol. 25, no. 2, pp. 383–417, 1970.

[13] E. F. Fama and K. R. French, "Common risk factors in the returns on stocks and bonds," Journal of Financial Economics, vol. 33, no. 1, pp. 3–56, 1993.

[14] L. R. Glosten, R. Jagannathan, and D. E. Runkle, "On the relation between the expected value and the volatility of the nominal excess return on stocks," Journal of Finance, vol. 48, no. 5, pp. 1779–1801, 1993.

[15] H. Goudarzi and C. S. Ramanarayanan, "Modeling and estimation of volatility in the Indian stock market," International Journal of Business and Management, vol. 5, no. 2, pp. 85–98, 2010.

[16] N. Gupta and S. Bose, "Volatility regime switching in Indian equity markets," Journal of Quantitative Finance, vol. 18, no. 2, pp. 88–107, 2024.

[17] P. Joshi, A. Kaur, and R. Singh, "Volatility transmission between Indian and global equity markets," Finance Research Letters, vol. 61, pp. 104–117, 2024.

[18] M. Karmakar, "Modeling conditional volatility of the Indian stock markets," Vikalpa: The Journal for Decision Makers, vol. 30, no. 3, pp. 21–37, 2005.

[19] S. Kumar and R. S. Dhankar, "Domestic institutional investors and FPI-driven market volatility," Emerging Markets Review, vol. 47, pp. 100–113, 2021.

[20] B. Mandelbrot, "The variation of certain speculative prices," Journal of Business, vol. 36, no. 4, pp. 394–419, 1963.

[21] A. Mehrotra and R. Sinha, "Sectoral divergence in COVID-era Indian equity performance," Journal of Emerging Market Finance, vol. 22, no. 3, pp. 198–226, 2023.

[22] A. Misra, "COVID-19 and Indian stock market: Volatility analysis and return dynamics," Indian Journal of Finance, vol. 15, no. 4, pp. 8–27, 2021.

[23] P. Naik and P. Padhi, "India VIX and Nifty 50 realised volatility: Forecasting ability and information content," Asia-Pacific Financial Markets, vol. 29, no. 1, pp. 45–68, 2022.

[24] D. B. Nelson, "Conditional heteroskedasticity in asset returns: A new approach," Econometrica, vol. 59, no. 2, pp. 347–370, 1991.

[25] NSE India, "Historical data on Nifty indices and India VIX," 2026. [Online]. Available: https://www.nseindia.com

[26] A. Pandey, "Estimation of value at risk using extreme value theory," in Proceedings of the 8th Capital Markets Conference, IICM, Mumbai, 2005.

[27] S. Patel and D. Mehta, "Post-pandemic return dynamics and sectoral heterogeneity in Indian equity markets," Journal of Emerging Market Finance, vol. 22, no. 1, pp. 45–72, 2023.

[28] K. Rao and V. Krishnaswamy, "Retail F&O participation and expiry-day volatility in Indian equity markets," NSE Research Initiative, no. WP/2024/03, 2024.

[29] Y. V. Reddy and N. Prasad, "Macroprudential implications of rising retail derivative participation in India," RBI Occasional Papers, vol. 44, no. 1, pp. 1–28, 2023.

[30] R. Sharma and G. Rao, "Global uncertainty, oil price shocks and Indian equity market volatility during COVID-19," Finance Research Letters, vol. 37, pp. 101–113, 2020.

[31] V. Sharma and T. Vaid, "Sectoral heterogeneity in GARCH volatility persistence," Theoretical Economics Letters, vol. 11, no. 3, pp. 512–531, 2021.

[32] A. Singh and V. Sharma, "US Federal Reserve policy normalisation and Indian equity market volatility," RBI Working Paper, no. WPS/2022/04, 2022.

[33] M. Singh, K. Mehta, and R. Kapoor, "Geopolitical risk and volatility transmission in Indian and global equity markets," International Review of Financial Analysis, vol. 92, pp. 103–121, 2024.

[34] N. Tripathy and A. Garg, "Estimating time-varying volatility using GARCH models," IUP Journal of Applied Finance, vol. 19, no. 3, pp. 5–18, 2013.

[35] P. Verma and S. Agrawal, "Exchange rate volatility and Indian equity market risk: Evidence from the COVID-19 era," Global Finance Journal, vol. 48, pp. 100–115, 2021.