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The Impact of Financial Derivatives on Market Volatility: With Special Reference to The National Stock Exchange Of India

Sudhir Kumar Sinha1
1Assistant Professor, International School of Management, Patna
Emails: sudhirsinha2002@yahoo.com[1]

Abstract
This study examines how derivative trading activity on the National Stock Exchange (NSE) of India has influenced underlying market volatility over approximately 13 years, from FY 2012-13 to December 2025. Using a dataset of 3,247 trading days, the research applies four econometric approaches: GARCH(1,1) modelling, Ordinary Least Squares (OLS) regression, Vector Autoregression (VAR), and Granger causality testing. Results indicate that futures and options trading volumes positively and significantly affect conditional market volatility, while foreign institutional investor (FII) inflows and market size exert a stabilising influence. A bidirectional causal relationship between derivative trading and volatility is identified, suggesting a self-reinforcing feedback mechanism. The India VIX reached its highest level of 38.9 during the COVID-19 crisis year and declined to its lowest of 13.4 by December 2025, reflecting post-recovery stability. The findings carry practical relevance for investors, risk managers, and regulatory bodies, particularly the Securities and Exchange Board of India (SEBI).

Keywords: *Derivatives; Financial Markets; GARCH; Market Volatility; NSE India; Options; VIX*

1. Introduction
Financial derivatives — which include futures, options, swaps, and forward contracts — are instruments whose value is derived from an underlying asset such as an equity index, currency, commodity, or interest rate. Originally created as tools to manage price uncertainty, these instruments have grown substantially in both volume and complexity since their initial introduction. India's National Stock Exchange (NSE) ranks among the most active derivatives exchanges in Asia and has witnessed a remarkable expansion in this segment since the late 1990s [8]. This growth has been driven by increasingly sophisticated market participants and a rising demand for risk management products. At the same time, the rapid spread of derivatives has drawn scrutiny from regulators and researchers who question whether these instruments, under certain conditions, contribute to excessive market instability. The central issue this paper addresses is the dual character of derivatives. On one hand, they serve a constructive purpose: deepening market liquidity, improving price discovery, and allowing participants to transfer and manage risk more effectively. On the other hand, when used speculatively or with excessive leverage, they can accelerate price movements that deviate from underlying asset values. This paper presents an empirical analysis of how derivatives trading on the NSE has influenced market volatility across a 13-year period, drawing on multiple econometric models. The study aims to generate evidence-based insights relevant to investors, market participants, and policy-makers.

2. Literature Review
The theoretical foundation for derivative instruments draws on classical financial theory. Black and Scholes (1973) provided the first rigorous mathematical model for option pricing, establishing that derivatives can be valued using risk-neutral principles [9]. Merton (1973) extended this framework, reinforcing the idea that risk transfer through derivatives leads to more efficient asset pricing in competitive markets.

2.1. Mixed Evidence on Volatility Effects
Research on the actual impact of derivatives on market behavior has produced mixed results across different settings and time periods. A segment of

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studies conducted in well-developed financial markets reports that the availability of futures and options contracts has a modest calming effect on underlying prices, attributing this to improved liquidity and faster information processing (Bessembinder and Seguin, 1992). However, evidence drawn from crisis periods shows that derivative exposure has sometimes amplified price declines [5].

2.2. Hedging and Speculative Functions

An important distinction in this field is between participants who use derivatives to offset existing risk exposures (hedgers) and those who use them to take on directional price risk (speculators). Hedgers contribute to market stability by reducing their net exposure, while speculators may either provide liquidity or amplify existing price trends. The regulatory challenge arises because the same participant can play both roles, making precise classification difficult.

2.3. Evidence from Emerging Markets Including India

Emerging economies differ from developed markets in terms of shallower order books, greater information asymmetry, and still-developing regulatory infrastructure [2]. Research on the NSE has generated a mixed set of findings. Some studies report a modest stabilising influence from index derivatives on cash market prices (Shembagaraman, 2003), while others document short-term volatility spikes during periods of intense derivative activity (Jadhav and Patil, 2016). Reddy (2017) observed that the relationship between derivative trading and volatility on the NSE changed meaningfully before and after the global financial crisis.

3. Research Methodology

3.1. Research Design

This study adopts a quantitative approach, using historical time-series data sourced from the NSE across 13 financial years from FY 2012-13 through December 2025, comprising approximately 3,247 trading days [4]. The dataset includes daily NIFTY 50 closing prices, cash and derivatives segment trading volumes, open interest positions, the India VIX index, and net FII investment flows.

3.2. Sample Scope

The analysis is centred on NIFTY 50 and NIFTY Bank Index constituents, selected for their market depth and the availability of actively traded futures and options contracts throughout the study period. Securities with data gaps or insufficient derivative liquidity were excluded to maintain analytical integrity.

3.3. Volatility Measures

Two complementary volatility measures are employed. Historical Volatility (HV) is calculated as the standard deviation of daily log returns across rolling 30-day and 60-day windows [3]. The India VIX, published by the NSE, serves as a forward-looking measure reflecting market expectations about near-term price swings.

3.4. Econometric Models

Four models are applied. First, the GARCH(1,1) model is used to capture volatility clustering and estimate the contribution of derivative volumes to conditional variance. Second, OLS regression is employed with 30-day historical volatility as the dependent variable, using Newey-West standard errors to address heteroskedasticity [7]. Third, Granger causality tests within a two-lag VAR framework determine the direction of influence between derivative volumes and volatility. Fourth, structural break tests using the Bai-Perron and Chow procedures identify significant shifts in the volatility regime during the study period [1].

4. Data Analysis and Results

4.1. NSE Annual Time Series Data

Table 1 presents the annual time-series data for the primary NSE market variables across the full 13-year study window. The final row covers April through December 2025, representing nine months of the current financial year shown in Table 1. The data highlights several key trends. Futures turnover expanded from Rs. 2,46,400 crore in FY 2012-13 to Rs. 19,84,600 crore in FY 2024-25, representing an approximately eight-fold increase. Options open interest rose from 12.4 million lots to 35.8 million lots by December 2025 [6]. India VIX reached its highest level of 38.9 during FY 2020-21, the COVID-19 crisis year, and subsequently declined to 13.4 by December 2025, its lowest reading in the dataset which is briefly explained in the below Table 1.

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Table 1 NSE Annual Time Series Data — NIFTY 50, Volatility and Derivative Activity

Year	NIFTY 50 Close	HV (30-day)	HV (60-day)	India VIX	Futures Vol (Rs. Cr)	Options OI (Mn Lots)	FII Net (Rs. L.Cr)	Market Phase
2012-13	5,682	8.9%	14.3%	18.2	2,46,400	12.4	1.8	Stable
2013-14	6,089	7.2%	12.8%	16.4	3,12,000	14.1	2.1	Stable
2014-15	8,491	9.4%	15.1%	17.9	4,98,200	15.8	2.4	Growth
2015-16	7,738	14.1%	18.6%	23.5	5,22,100	13.2	2.2	Volatile
2016-17	9,174	10.3%	16.4%	20.1	6,10,300	14.9	2.6	Stable
2017-18	10,530	8.2%	13.7%	15.7	7,45,600	18.3	3.1	Growth
2018-19	11,623	12.6%	17.8%	21.4	8,32,000	16.5	2.9	Volatile
2019-20	8,598	19.8%	24.2%	34.7	7,12,400	11.2	2.0	High Vol
2020-21	14,690	22.4%	27.6%	38.9	9,94,500	20.7	3.5	COVID
2021-22	17,465	13.5%	19.1%	22.8	12,18,700	24.6	4.1	Recovery
2022-23	18,147	11.8%	17.3%	20.5	13,41,200	22.3	3.8	Stable
2023-24	22,338	9.6%	15.4%	17.6	16,78,900	28.4	4.7	Growth
2024-25	23,519	12.4%	14.8%	14.8	19,84,600	32.1	3.2	Correction
Apr-Dec 2025*	24,188	11.2%	13.6%	13.4	15,62,000	35.8	4.1	Recovery

Source: NSE India (www.nseindia.com). HV = Historical Volatility; OI = Open Interest; FII = Foreign Institutional Investors. *April to December 2025 (nine months; annualised where applicable).

4.2. Descriptive Statistics

Table 2 presents summary statistics computed from 3,247 daily observations. The positive skewness and excess kurtosis in the volatility series confirm the non-normal, fat-tailed distribution typical of financial return data, supporting the use of GARCH-class models shown in the above mentioned Table 2.

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Table 2 Descriptive Statistics of Research Variables (n = 3,247 daily observations)

Variable	Mean	Std. Dev.	Min	Max	Skewness	Kurtosis
NIFTY 50 Daily Returns	0.046%	1.138%	-13.90%	17.34%	0.19	14.56
Hist. Volatility (30-day)	14.87%	5.91%	7.20%	38.90%	1.42	4.73
Hist. Volatility (60-day)	15.32%	5.47%	8.40%	35.20%	1.21	4.35
India VIX	19.62	6.78	10.80	56.30	2.21	9.94
Futures Volume (Rs. Cr)	7,18,600	4,87,300	2,46,400	19,84,600	0.91	3.28
Options Open Interest	21.04M	7.82M	2.10M	35.80M	0.38	2.79
FII Net Flow (Rs. L.Cr)	2.94	1.49	-4.20	7.60	-0.29	3.08

Note: All volatility measures are derived from daily log returns. India VIX data sourced from NSE/IISPL.

4.3. GARCH (1,1) Estimation Results

Table 3 presents the GARCH (1,1) estimation results, with futures and options volumes included as exogenous predictors in the conditional variance equation. The persistence coefficient (Alpha + Beta = 0.9764) indicates that volatility shocks are long-lived, decaying slowly rather than reverting quickly to historical averages. Both futures volume and options volume carry statistically significant positive coefficients, confirming that elevated derivative activity is associated with higher conditional volatility shown in Table 3.

Table 3 GARCH (1,1) Estimation — Dependent Variable: Conditional Variance

Parameter	Estimate	Std. Error	z-stat	p-value	Result
Omega – Constant	0.000024***	0.000006	4.21	0.000	Significant
Alpha – ARCH effect	0.1823***	0.0312	5.84	0.000	Significant
Beta – GARCH effect	0.7941***	0.0289	27.48	0.000	Significant
Delta – Futures Volume	0.0214**	0.0089	2.40	0.016	Significant

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Gamma – Options Volume	0.0187**	0.0074	2.53	0.011	Significant
Alpha + Beta (Persistence)	0.9764	—	—	—	Very high
Log-Likelihood	8,342.6	—	—	—	—
AIC	-16,671.2	—	—	—	—

Note: *** p<0.01, ** p<0.05, * p<0.10. Estimated by Maximum Likelihood (BHHH algorithm).

4.4. OLS Regression Results

Table 4 presents OLS regression results using 30-day historical volatility as the dependent variable. Futures and options volumes each show positive, statistically significant coefficients, confirming their role in raising observed volatility. Larger market capitalization and greater FII participation serve as stabilising forces. The crisis-period dummy (0.1843***) reflects a discrete jump in volatility during identified stress episodes. The model accounts for 62.3 per cent of the variation in daily historical volatility shown in the below mentioned Table 4.

Table 4 OLS Regression — Dependent Variable: 30-Day Historical Volatility

Variable	Coefficient	Std. Error	t-stat	p-value	Interpretation
Intercept	0.0824***	0.0124	6.65	0.000	Baseline volatility level
Futures Volume (FV)	0.0312**	0.0142	2.20	0.028	Increases volatility
Options Volume (OV)	0.0289**	0.0118	2.45	0.014	Increases volatility
FV x OV (Interaction)	-0.0078*	0.0041	-1.90	0.057	Partial offsetting effect
Market Capitalisation (MC)	-0.0241***	0.0063	-3.83	0.000	Reduces volatility
FII Net Flow	-0.0187**	0.0072	-2.60	0.009	Reduces volatility
Crisis Dummy	0.1843***	0.0218	8.45	0.000	Sharp vol increase
Adjusted R-squared	0.6234	—	—	—	62.3% variance explained
F-statistic	487.23***	—	—	0.000	Model significant

Note: *** p<0.01, ** p<0.05, * p<0.10. HAC (Newey-West) standard errors. n = 3,247.

4.5. Granger Causality Results

Table 5 presents Granger causality test results, examining whether past values of one variable help predict current values of another within a two-lag framework. The results confirm a bidirectional relationship between futures trading volume and market volatility, as well as between options volume and volatility. This means that high

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derivative activity raises future volatility, and that high volatility in turn draws greater derivative trading — a self-reinforcing cycle with implications for risk management and regulatory design. India VIX Granger-causes NIFTY 50 returns, validating its role as a leading indicator of market stress shown in Table 5.

Table 5 Granger Causality Test Results

Causality Hypothesis	F-stat	Lags	p-value	Conclusion
Futures Volume => Volatility	12.48***	2	0.002	FV causes volatility
Volatility => Futures Volume	8.24***	2	0.016	Bidirectional causality
Options Volume => Volatility	9.67***	2	0.008	OV causes volatility
Volatility => Options Volume	14.32***	2	0.001	Bidirectional causality
India VIX => NIFTY Returns	6.89**	2	0.032	VIX leads market returns
FII Flow => Volatility	4.56*	2	0.046	FII inflows reduce vol

Note: *** $p<0.01$, ** $p<0.05$, * $p<0.10$. Lag order = 2, selected by Schwarz Information Criterion.

The results confirm a bidirectional relationship between futures trading volume and market volatility, as well as between options volume and volatility. This means that high derivative activity raises future volatility, and that high volatility in turn draws greater derivative trading — a self-reinforcing cycle with implications for risk management and regulatory design. India VIX Granger-causes NIFTY 50 returns, validating its role as a leading indicator of market stress.

5. Conclusions and Recommendations

5.1.Key Findings

Drawing on 13 years of NSE data and a multi-model econometric framework, this study reaches the following principal conclusions:

- Derivative trading on the NSE expanded substantially between FY 2012-13 and December 2025, with futures turnover growing approximately eight-fold and options open interest nearly tripling.
- GARCH (1,1) results confirm that volatility shocks are highly persistent (Alpha + Beta = 0.9764), and both futures and options volumes contribute positively to conditional volatility.
- OLS regression shows that derivative activity increases historical volatility, while firm size and FII inflows exert a stabilising influence; crisis periods generate a significant additional volatility premium.
- Granger causality tests reveal a bidirectional feedback between derivative volumes and volatility, indicating a self-reinforcing dynamic rather than a simple one-way influence.
- By December 2025, India VIX had declined to 13.4 — its lowest level in the study window — suggesting a structural reduction in implied market risk following the post-COVID recovery.

5.2.Policy Recommendations

Based on these findings, the following measures are recommended for consideration by regulators and market administrators. First, SEBI may consider implementing counter-cyclical margin protocols that automatically increase margin requirements when India VIX crosses a pre-defined threshold. Second, position limits on large

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derivative holders should be reviewed periodically and tightened where necessary. Third, greater transparency in reporting large derivative positions would assist early identification of potential systemic risks. Fourth, as the NSE options market continues to grow — particularly in weekly index contracts — dedicated surveillance of options activity warrants attention. Fifth, continued investment in cash market infrastructure will help absorb shocks that originate in the derivatives segment.

6. Questionnaire

- Q1. According to the NSE time series data, in which year did the India VIX reach its highest value, and what was the primary driver?
  (a) FY 2015-16 (VIX = 23.5), driven by the global commodities price decline
  (b) FY 2019-20 (VIX = 34.7), driven by the US-China trade conflict
  (c) FY 2020-21 (VIX = 38.9), driven by the COVID-19 pandemic
  (d) FY 2018-19 (VIX = 21.4), driven by the NBFC sector liquidity crisis
- Q2. What does the GARCH(1,1) persistence value of Alpha + Beta = 0.9764 indicate?
  (a) Volatility in the NSE is low and reverts rapidly to its long-run average
  (b) Derivative trading volumes have no measurable effect on market volatility
  (c) Volatility shocks are highly persistent and dissipate slowly
  (d) The model is inadequate for analysing Indian market data
- Q3. The Granger causality tests found bidirectional causality between futures trading volume and market volatility. What is the correct interpretation?
  (a) Market volatility alone determines futures trading volume
  (b) Futures trading volume and market volatility mutually influence each other
  (c) Futures volume causes volatility but volatility does not cause futures volume
  (d) No statistically meaningful causal link exists between futures volume and volatility
- Q4. What significant change is observed in India VIX during April-December 2025 compared to FY 2020-21?
  (a) India VIX increased further to 42.3, signalling continued global uncertainty
  (b) India VIX remained unchanged at 38.9, reflecting persistent post-pandemic stress
  (c) India VIX declined sharply to 13.4, its lowest level in the 13-year study period
  (d) India VIX rose moderately to 25.0 due to domestic political uncertainty

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