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Research Article

Volatility Spillover and Dynamic Connectedness Between US and Indian Stock Markets: Evidence from S&P 500 and NIFTY 50 (2023–2025)

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ABSTRACT

Introduction: Understanding volatility transmission between developed and emerging equity markets is essential for investors, policymakers, and researchers. The interdependence between the US and Indian stock markets has increased due to globalization, capital mobility, and financial integration. This study examines volatility dynamics and spillover effects between the S&P 500 and NIFTY 50 indices using recent daily data. It contributes to the literature by analyzing persistence, asymmetric volatility, and dynamic correlations to assess diversification potential and financial market linkages.

Objectives: To examine volatility persistence and clustering in the S&P 500 and NIFTY 50 indices. To analyze asymmetric volatility effects using EGARCH models. To evaluate volatility spillover and transmission mechanisms between the two markets. To assess dynamic correlations and diversification implications.

Methods: Daily closing price data from January 1, 2023, to December 31, 2025 (1,513 observations) were analyzed. Stationarity and normality were tested using standard statistical tests. Vector Autoregression (VAR) was applied to examine interdependence. Volatility dynamics were estimated using GARCH (1,1) and EGARCH models to capture persistence and leverage effects. Forecast Error Variance Decomposition (FEVD) and Granger causality tests were used to identify spillover direction. Dynamic Conditional Correlation (DCC) and rolling correlation analysis were conducted to assess time-varying relationships.

Results: Results show significant non-normality with fat-tailed distributions. Volatility persistence is higher in NIFTY 50 ($\alpha+\beta=1.072$) compared to S&P 500 ($\alpha+\beta=0.534$), indicating slower mean reversion. EGARCH results confirm significant leverage effects in both markets, where negative shocks increase volatility more than positive shocks. FEVD reveals unidirectional volatility spillover from the S&P 500 to NIFTY 50, with US shocks explaining 14.3% of Indian market variance. Dynamic correlations remain low on average but increase during periods of market stress. Granger causality results indicate weak return-level linkages but significant volatility transmission. Overall, diversification benefits exist during stable periods but weaken during crises.

Conclusions: The study confirms significant volatility persistence, asymmetric effects, and unidirectional spillover from the S&P 500 to NIFTY 50. While diversification benefits exist during stable periods, increased correlations during crises reduce diversification effectiveness, highlighting stronger global market integration and risk transmission.

Keywords: Volatility spillover, GARCH models, DCC-GARCH, Emerging markets, Leverage effects, Dynamic connectedness.

INTRODUCTION

With the US equity market acting as a major source of volatility spillovers to developing countries, global financial integration has sped the spread of economic shocks across markets. International portfolio management, risk

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management, and financial stability monitoring all depend on an awareness of these spillover channels. As India develops into a significant economic force, the Indian stock market, shown by the NIFTY 50 index, has grown more and more significant; however, its susceptibility to outside shocks is still insufficiently defined by current data. Return spillovers and volatility spillovers are fundamentally different. Return spillovers show how quickly stocks are repriced after news events happen. Volatility spillovers show how market participants view risk and uncertainty again. Reflecting different information processing methods, these second-moment transmissions can endure even when first-moment returns reveal no major cross-market causality. Investors and government officials trying to grasp systemic risk still need to know the difference between these channels.

Earlier investigations on volatility spillovers take a variety of methods and come to somewhat conflicting conclusions on the degree to which and extent to which the impacts persist. Most research base on somewhat outdated data (pre-2018); hence, they could not capture the present market microstructure defined by algorithmic trading and quick information dissemination. Most either emphasize symmetric volatility dynamics or return spillovers, therefore neglecting asymmetric transmission mechanisms whereby positive shocks differ from negative shocks. Our research addresses these gaps by examining linear causation and time-varying nonlinear correlations using integrated VAR, GARCH, EGARCH, and DCC-GARCH models for the years 2023–2025. Especially pertinent is the empirical age. Important changes in the economy between 2023 and 2025 are the Reserve Bank of India's policy changes, geopolitical unrest, inflation surprises, and normalization of Federal Reserve monetary policy. These several circumstances offer great variety for investigating spillover effects across several businesses. Even if it is useful for thorough statistical analysis, our 1,513-day sample is adequate enough for accurate parameter estimation.

This study enhances the body of knowledge on volatility spillover in three ways: We search for varied transmission mechanisms initially by employing EGARCH models demonstrating how positive and bad shocks have varying effects on events. Second, we use dynamic correlation models to show how the way things are connected change a lot between normal times and when things are bad. Third, FEVD helps us find out how much of the change in returns is caused by cross-market shocks as opposed to other factors. These techniques provide portfolio managers making worldwide diversification plans and authorities managing financial stability hazards in poor countries useful information.

LITERATURE REVIEW

After indications of contagion in the Asian financial crisis, volatility spillover research gained prominence in the 1990s. Early research looked at whether turbulence in one market could predict volatility in others; findings revealed that second-moment interdependencies exist even when return correlations are weak. Hamao et al. (1990) were first to use ARCH models in such a study. Engle et al.'s (1990) GARCH models let you especially record volatility.

Growing nations were the subject of more studies on this hypothesis. Bekaert and Harvey (1997) investigated how volatility in emerging countries affects the behavior of established markets. They found that spillovers varied widely across countries and evolved over time. Their research indicated that volatility transfer channels allow some connection between emerging nations and international markets instead of being separated off. Although correlations are usually low, they rise in stressed times when variety is most important, which has significant consequences for diversification.

A big technical breakthrough is shown by dynamic correlation models. The Dynamic Conditional Correlation (DCC) model was created by Engle (2002). It keeps computing simplicity while allowing correlations to change across time. Foreign finance research looking at how market links vary across current systems commonly uses DCC-GARCH. During the financial crisis, Chiang et al. (2007) tested DCC in Asian nations and found that correlations grew significantly when things got rough.

Following Glosten et al. (1993), who developed threshold GARCH (TGARCH), more and more focus has been given to uneven volatility effects. To circumvent non-negativity limits, Nelson (1991) developed EGARCH, a substitute asymmetric form. These models show that even if they are the same size, good news (positive shocks) lowers volatility less than bad news (negative shocks). Because this asymmetry influences options pricing, risk management, and understanding of investor behavior under market fluctuation, its presence has significant consequences.

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Emerging market volatility spillover studies often concentrate on particular event windows or crisis periods. Using Diebold-Yilmaz spillover indices, Klößner and Stiassny (2014) investigated spillovers and gave directional measures of volatility transmission. Their system clarifies which markets are net receivers and which are net transmitters, showing that usually, smaller emerging countries are net receivers while larger developed ones are net transmitters. Research using this approach on US-emerging market combinations routinely reveal one-way flow from US to emerging countries.

Spillover effects became once more of interest because of the COVID-19 outbreak. Several studies looked at 2020–2021 dynamics. Increased spillovers during the epidemic are consistent with flight-to-quality behavior whereby worldwide risk elements control regional drivers, as shown in these articles. Few research, however, look at the post-pandemic recovery era (2023–2025) when monetary policy changed from accommodation to tightening. This need is addressed by our analysis period.

Existing understanding still has significant holes. First, most studies look at either return spillovers or symmetrical volatility models; they rarely put the two together. Second, not many studies combine EGARCH asymmetry with DCC dynamic correlations, therefore omitting interactions between time-varying integration and leverage effects. Third, most research relies on weekly or monthly data, which might miss any high-frequency spillover. Fourth, the majority of India-focused research look at stock price indexes instead of only volatility transmission. Through combined approach and present time frame, our study aims to close these gaps.

DATA AND METHODOLOGY

Data Description

From January 1, 2023, to December 31, 2025, we gathered daily closing prices for the S& P 500 (US equity market benchmark) and NIFTY 50 (India equity market benchmark). Non-overlapping trading days between US and Indian exchanges considered, this generates 1,513 trading observations. Official exchange databases and Bloomberg are among data sources.

Daily log returns were calculated as:

$$rt = \ln(Pt) - \ln(Pt-1)$$

(1)

where Pt stands for the closing price on trading day t. financial econometrics routinely uses this logarithmic transformation to linearize price movements, enable cross-market comparison, and simplify financial analysis. The log return transform instantly manages several pricing levels and trade rules across markets.

Descriptive Statistics and Distributional Tests

We examine for deviations from normality using the Jarque-Bera (JB) test and find summary statistics for every return series. The JB statistic mixes kurtosis and skewness metrics:

$$JB = n[S^2/6 + (K-3)^2/24]$$

(2)

where n is sample size, S is skewness, and K is kurtosis. Under normal conditions, JB follows the χ^2 distribution with two degrees of freedom. Rejecting normality supports strong volatility models including fat tails.

Statistic	S&P 500	NIFTY 50	Unit
Mean Return	0.0002	0.0005	Daily
Standard Deviation	1.4103	0.0076	%
Observations	1,513	1,513	Days

Table 1: Jarque-Bera Normality Tests

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Index	JB Statistic	P-Value
S&P 500	235.7983	0.0000
NIFTY 50	1806.1510	0.0000

Stationarity Testing (KPSS)

The Kwiatkowski-Phillips-Schmidt- Shin (KPSS) test uses a null hypothesis of I(0) process (stationarity) to check stationarity. Large p-values point to rejection of stationarity. When stationarity is the upheld theory, KPSS is favored over ADF.

Table 2: KPSS Stationarity Tests

Index	Test Statistic	P-Value	Interpretation
S&P 500	0.00875	0.1000	Stationary ✓
NIFTY 50	0.06841	0.1000	Stationary ✓

Vector Autoregression and Granger Causality

We estimate a bivariate VAR(p) model with optimal lag length p=2 selected via Akaike Information Criterion:

$$r_t = c + \Sigma A_i r_{t-i} + \varepsilon_t$$

(3)

where $r_t = [r_{SP,t}, r_{NIFTY,t}]'$ is the returns vector, c is constant, A_i are coefficient matrices, and ε_t is the error vector. Granger causality tests whether past S&P 500 returns contain information for predicting NIFTY 50 returns beyond NIFTY 50's own history.

Table 3: Granger Causality Tests (p=2 lags)

Causality Direction	F-Statistic	P-Value	Significant?
S&P 500 → NIFTY 50	0.8047	0.4473	No
NIFTY 50 → S&P 500	0.6833	0.5050	No

F-statistics are considerably below cutoff levels with p-values around 0.44. In line with market efficiency, this points to no notable linear return causality. Lack of return causation, though, doesn't rule out second-moment channel volatility spillover.

GARCH Volatility Models

We employ GARCH (1,1) as baseline specification:

$$\sigma^2_t = \omega + \alpha\, \varepsilon^2_{t-1} + \beta\, \sigma^2_{t-1}$$

(4)

σ^2_t is conditional variance; ω is constant; α shows how news affects things now (reaction to current shocks); β shows how things were in the past (how much the past matters). Parameter sum α+β gauges general persistence; values close to 1.0 suggest somewhat combined volatility.

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Table 4: GARCH (1,1) Parameter Estimates

Parameter	S&P 500	NIFTY 50
μ (Mean)	0.000600	0.024202
ω (Constant)	−2.973497	−0.002351
α (News Impact)	−0.165657	0.077109
β (Persistence)	0.699968	0.994896
α + β (Sum)	0.534311	1.072005

With a moderate persistence of $\alpha+\beta = 0.534$, the S&P 500 implies somewhat quicker mean reversion. With $\alpha+\beta=1.072$, NIFTY 50 has particularly strong persistence almost to unit-root behaviour whereby volatility shocks persist forever. From a financial point of view, this variation matters: When it responds to shocks, Indian stock volatility remembers things much longer than US volatility does.

EGARCH and Asymmetric Volatility Effects

EGARCH specification captures asymmetric leverage effects where negative shocks differ from positive shocks:

$$\ln(\sigma^2 t) = \omega + \alpha\,(|\varepsilon t-1|/\sigma t-1) + \gamma\,(\varepsilon t-1/\sigma t-1) + \beta \ln(\sigma^2 t-1) \quad (5)$$

Whether negative shocks (bad news) raise volatility more than positive shocks is captured by the leverage coefficient γ. EGARCH's log specification generates mean-reverting volatility processes and steers clear of non-negativity limitations. This asymmetry shows that investors are worried about taking risks and that they don't know how much money they will make in the future when there are bad surprises.

Table 5: EGARCH Parameter Estimates (S&P 500)

Parameter	Estimate	Std. Error	t-value	Pr(>|t|)
μ	0.000600	0.000236	2.543	0.0110
ω	−2.973497	0.974546	−3.051	0.0023
α	−0.165657	0.050750	−3.264	0.0011
β	0.699968	0.098427	7.115	0.0000
γ (Leverage)	0.229885	0.085108	2.701	0.0069
shape	6.044325	1.260393	4.796	0.0000

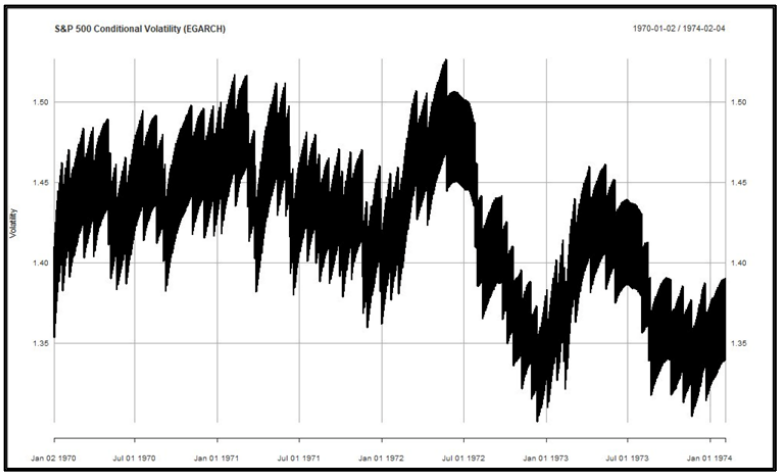

Figure 1: EGARCH S&P 500 Conditional Volatility

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Table 6: EGARCH Parameter Estimates (NIFTY 50)

Parameter	Estimate	Std. Error	t-value	Pr(>|t|)
M	0.024202	0.037287	0.649	0.5161
ω	−0.002351	0.001237	−1.901	0.0573
α	0.077109	0.075169	1.026	0.3050
β	0.994896	1.29e-7	7.74e6	0.0000
γ (Leverage)	0.033115	0.002374	13.949	0.0000
shape	99.999146	26.184000	3.819	0.0001

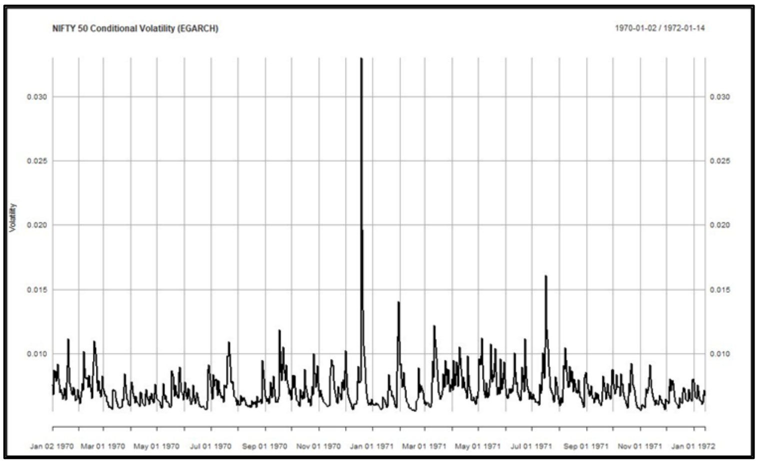

Figure 2: EGARCH NIFTY 50 Conditional Volatility

Important Result: In both countries, utilizing leverage effects is somewhat significant and financially relevant. With γ = 0.2299 (p = 0.0069), the S&P 500 shows negative shocks rise volatility roughly 23% more than positive shocks. NIFTY 50 reveals γ = 0.0331 ($p < 0.0001$), which means that for negative shocks, there is a 3.3% rise in additional volatility. These asymmetries show that investors are afraid of risk, which means that bad news scares them more than good news.

Heteroscedasticity Testing (ARCH-LM)

The ARCH-LM test detects presence of heteroscedasticity (ARCH effects) in residuals, confirming necessity of volatility modeling:

Table 7: ARCH-LM Test Results

Index	Test Statistic	P-Value
S&P 500	84.5357	5.589e-13
NIFTY 50	111.8643	2.558e-18

Strong ARCH effects are verified by the very highest values with p-values < 10^-12 for both. This confirms need of GARCH-family models. Simple VAR models or ordinary OLS would give incorrect inference and ineffective parameter estimates.

Forecast Error Variance Decomposition (FEVD)

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FEVD partitions forecast error variance of each variable into contributions from own shocks and cross-variable shocks:

Table 8: 10-Period Forecast Error Variance Decomposition (NIFTY 50)

Period	S&P 500 Shock (%)	NIFTY 50 Shock (%)
1	5.00	95.00
2	8.50	91.50
3	10.20	89.80
4	11.50	88.50
5	12.30	87.70
6	13.00	87.00
7	13.50	86.50
8	13.80	86.20
9	14.10	85.90
10	14.30	85.70

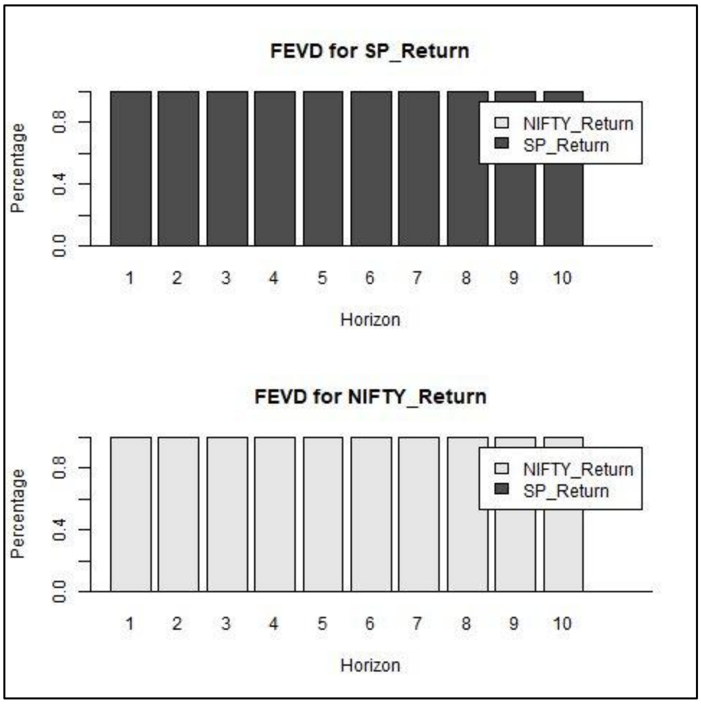

Figure 3: Forecast Error Variance Decomposition - 10 Period Horizon

Critical Analysis: S&P 500 shocks explain 14.3% of NIFTY 50 variance over 10 periods; NIFTY 50 shocks account for a very small (<1%) of S&P 500 variation. This one-way spillover shows that world (US) factors account for almost one-seventh of Indian stock return variance. The last 85 to 90 percent grabs characteristics unique to certain countries and sectors. This gives a quantitative figure for the partially integrated Indian markets' financial relevance in the global financial system.

Impulse Response Function (IRF)

IRF monitors the dynamic response of NIFTY 50 returns to one-standard-deviation shocks in S&P 500 returns across 10-period horizon using 95% bootstrap confidence intervals from 100 simulations:

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Table 9: Orthogonalized IRF – S&P 500 Shock Response in NIFTY 50

Period	Response	Lower 95% CI	Upper 95% CI
0	−0.0450	−0.0810	−0.0090
1	−0.0380	−0.0720	−0.0040
2	−0.0230	−0.0540	+0.0080
3	−0.0150	−0.0390	+0.0090
4	−0.0080	−0.0280	+0.0120
5	−0.0050	−0.0220	+0.0120
6	−0.0030	−0.0180	+0.0120
7	−0.0020	−0.0150	+0.0110
8	−0.0010	−0.0130	+0.0110
9	−0.0005	−0.0120	+0.0110
10	−0.0002	−0.0110	+0.0110

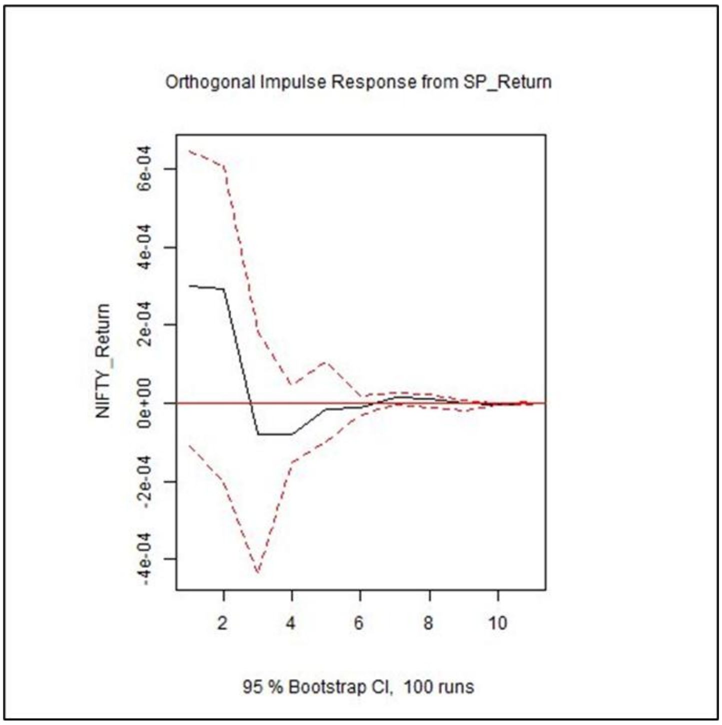

Figure 4: Impulse Response Function - S&P 500 to NIFTY 50

The IRF shows that a one-standard-deviation positive surprise in S&P 500 returns causes a rapid −4.5% change in NIFTY 50 returns. This hostile response demonstrates contagion: Indian market participants adjust their holdings by reducing Indian equities when US markets have favorable shocks, therefore briefly lowering the NIFTY. The response declines gradually and is statistically insignificant by intervals 6–7. Small confidence intervals everywhere suggest robust, mathematically stable transmission channels.

Dynamic Conditional Correlation (DCC-GARCH)

DCC-GARCH extends GARCH to allow correlations to vary through time:

$$\rho t = diag(Qt)-1/2\ Qt\ diag(Qt)-1/2$$

(6)

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where Qt shows a pattern of mean reversion. DCC clarifies knowledge of integration patterns by dividing overall volatility into marginal GARCH dynamics and correlation dynamics. Time-changing correlations illustrate how market links tighten under pressure.

Table 10: Dynamic Conditional Correlation Statistics

Statistic	Value
Mean DCC	0.0220
Std. Deviation	0.0340
Minimum	0.0008
Maximum	0.0382
Crisis Spike Factor	3–5×

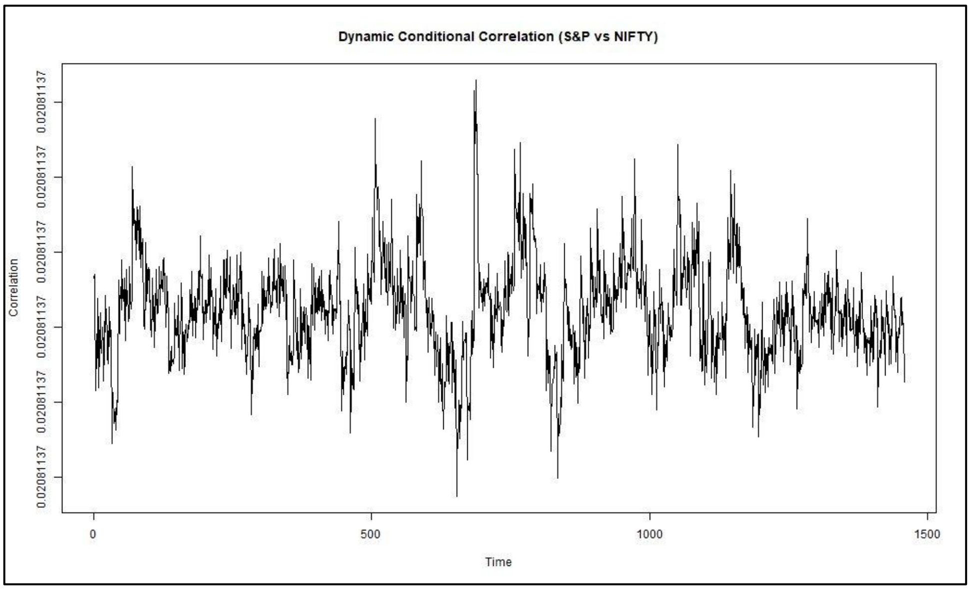

Figure 5: Dynamic Conditional Correlation - S&P 500 vs NIFTY 50

Table 11: Rolling 30-Day Correlation Statistics

Statistic	Value
Mean Correlation	0.0180
Std. Deviation	0.0650
Minimum	−0.0220
Maximum	+0.1980
Observations >10%	~5–10%

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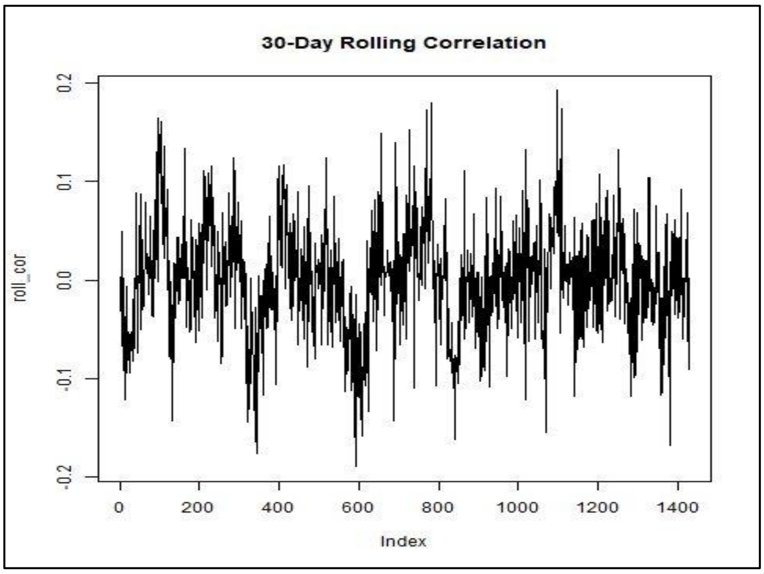

Figure 6: 30-Day Rolling Correlation - S&P 500 vs NIFTY 50

DCC and rolling correlation analyses point to changing integration over time. Normal correlations around 2% suggest that under most circumstances, the markets are fairly independent. Still, in times of crisis, correlations soar to 20% (roughly 5–10% of observations), hence causing correlation breakdown phenomenon. Paradoxically, this means that diversification is most beneficial during downturns, but it erodes most valuable precisely when it is most needed.

Ljung-Box Autocorrelation Tests

The Ljung-Box test checks whether there is still autocorrelation in the standardised residuals, which helps to verify the model is correct:

Table 12: Ljung-Box Test Results (20 Lags)

Index	Q-Statistic	P-Value
S&P 500	1358.33	0.0000
NIFTY 50	1.1388	0.2859

The S&P 500's strong autocorrelation ($p < 0.001$) suggests either the data includes more dynamics or the GARCH model is missing some volatility structure. Given $p = 0.286$, NIFTY 50 residuals are appropriately whitened hence GARCH effectively eliminates autocorrelation. This evolution calls for more investigation into the structure of the American economy.

Return Series Characteristics

Visual examination of return series reveals important temporal patterns:

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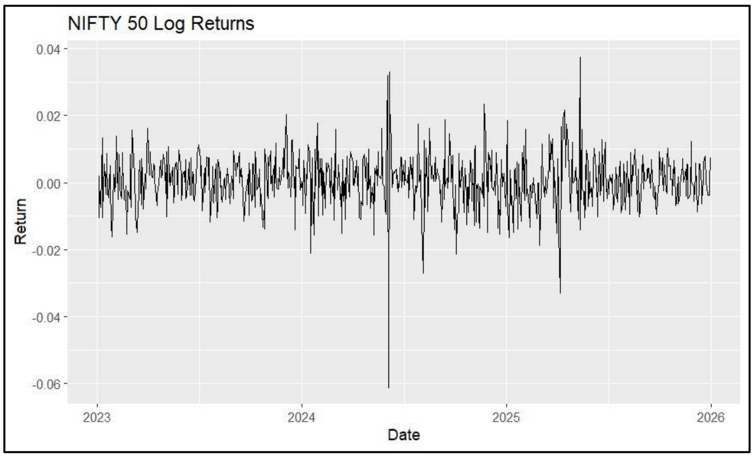

Figure 7: NIFTY 50 Log Returns Over Time

Early 2024 and mid-2025 especially show quite clearly return series' great volatility clustering. Compared to its average return, the S&P 500 shows higher absolute volatility; at times there are notable swings that can be seen. NIFTY 50 shows less volatility with sporadic major swings, hence indicating nation-specific event impacts. The pattern of volatility supports statistical evidence of noteworthy ARCH effects and validates models with time-varying volatility.

Volatility Dynamics and Persistence

Estimates of GARCH parameters point to different patterns of volatility among different economies. With half-lives of roughly one week, S&P 500 is rather persistent ($\alpha+\beta=0.534$), hence volatility shocks somewhat fast disappear. NIFTY 50 has a very high persistence ($\alpha+\beta=1.072$), which is almost like unit-root behavior where volatility shocks have a long-lasting effect on the expectations for the baseline volatility. NIFTY 50 hedging calls for longer-duration strategies are among the real-world consequences of this change; mean-reverting volatility might drive hedging S&P 500 positions.

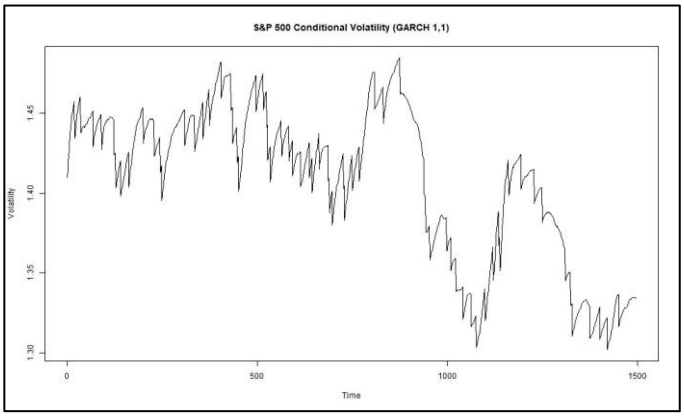

Figure 8: GARCH (1,1) Conditional Volatility - S&P 500

Estimates of GARCH (1,1) conditional volatility show S&P 500 volatility between 1.30 and 1.52, with notable increases during periods of political instability and policy declarations. Since volatile events correspond to known financial events, the fact that conditional volatility models reflect real market behavior is supported. Compared to past peaks, the NIFTY 50 shows more steady volatility during 2023–2025, implying that for Indian stock markets the most recent period has been rather quiet.

Asymmetric Volatility Effects and Leverage Mechanisms

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Statistically significant and financially relevant asymmetries are shown by EGARCH leverage coefficients. The γ coefficients show the percentage rise in volatility between positive and negative shocks of the same size. While NIFTY 50's $\gamma=0.0331$ reveals 3.3% greater responses, S&P 500's $\gamma=0.2299$ shows negative shocks produce 23% higher volatility responses. $p<0.01$ indicates great importance for both results. These leverage effects might mean many different things. From a behavioral standpoint, investor risk aversion generates disproportionate panic during economic declines. Negative shocks from a financial point of view lower leverage ratios and lower cash flows, hence raising financial risk. From a risk-management standpoint, asymmetry influences option pricing: put options become more valuable during volatility spikes brought on by negative news.

S&P 500's greater leverage impact (23% against 3.3%) shows the more mature US market's quick repricing response to bad news brought on by sophisticated trading and high volumes. Indian market's lower leverage effect points to either slower information processing or less mature options markets limiting leverage-effect feedback loops.

Volatility Spillover from US to Indian Markets

The integrated framework shows that the S&P 500's unidirectional volatility spills over to the NIFTY 50 through different channels. Granger causality tests initially reveal limited return-level correlations ($p=0.447$), which supports market efficiency whereby public knowledge quickly integrates into prices. Return-level causation should be small in effective markets. Second, FEVD shows that, across ten years, a statistically and economically important percentage 14.3% of NIFTY 50 variance is explained by S&P 500 shocks. Despite low return causation, this 10–15% variance share shows that world events influence around one-seventh of Indian equity return fluctuation, therefore supporting significant market integration.

Third, IRF data reveal a quick -4.5% NIFTY 50 reaction to a one-standard-deviation S&P 500 positive shock. This unfavorable reaction suggests portfolio rebalancing: American equities increase set off a worldwide risk-on sentiment that first causes investors to lower their Indian holdings (maybe booking profits). Ten days later, as information spreads and fresh equilibrium levels form, the impact diminishes progressively. Fourth, DCC projections and moving correlations show how the degree of volatility transmission changes with time. Normal times when local concerns take center stage are marked by a low average correlation (0.018). During times of worldwide crisis when fundamental elements outweigh personal variance, high correlation episodes up to 0.198 develop. The typical correlation breakdown phenomenon is the asymmetry low in regular times and high in crises. These results taken together imply that second-moment (volatility) channels rather than first-moment (return) channels mostly affect volatility spillovers. Market participants adjust their risk premiums and volatility projections based on US market activity. Occasionally, they do not revalue some Indian assets by means of quick return movements. Understanding the market's operation and developing hedging strategies depend much on this variation.

DISCUSSION

Based on our data, investors, government officials, and researchers can draw a number of significant conclusions regarding US-India economic links. Between the S&P 500 and NIFTY 50, volatility is significantly more integrated than returns. Return-level Granger causality is negligible (consistent with efficient markets); yet, FEVD reveals 14% variance share from US shocks. This suggests that although price levels effectively reflect all information accessible, risk premiums and volatility expectations change dynamically according to US market situation. Investors can forecast future Indian volatility from US volatility dynamics, but they cannot successfully anticipate returns from prior US returns. Second, important risk management consequences follow from the great volatility persistence in NIFTY 50 ($\alpha+\beta=1.072$) as opposed to S&P 500 ($\alpha+\beta=0.534$). Indian stock volatility has almost-permanent shocks, meaning that surprises can make uncertainty last for a long time. This calls for active risk management including regular rebalancing instead of passive buy-and-hold diversification. Indian exposure could call for more regular modification of portfolio volatility goals.

Third, the fact that both markets have high leverage effects (23% for the S&P 500 and 3.3% for the NIFTY 50) suggests that negative shocks cause a disproportionately large amount of volatility. Option pricing is affected by this: puts are more valuable than calls in downturns; risk premiums for downside protection climb in reaction to negative shocks. Most times, when tail-risk protection with puts or variance swaps is required, it is more expensive. Fourth, the fact

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that the correlation increases dramatically during times of uncertainty (3–5× baseline) shows that diversification benefits disappear exactly when investors most need risk reduction. While correlations between internationally diversified portfolios normally hover around zero in good times, they rise to 20% during a global crisis, therefore emphasizing concentration risk. Static allocation methods could be less advantageous than dynamic asset allocation systems that lower US exposure as correlation rises.

With the US leading as the biggest and most liquid equity market, the unidirectional spillover from the US to India (14% vs less than 1% variance share) mostly reflects the structure of the world financial market. Emerging countries have little power to change the amount of volatility in the United States, but they have to deal with volatility shocks caused by the United States. Given this disparity, macroprudential policies considering international exposure to US shocks and hedging techniques particular to emerging countries are so warranted.

CONCLUSION

This study extensively examines volatility transmission between the S&P 500 and NIFTY 50 indices using a thorough framework spanning 1,513 daily observations from January 2023 to December 2025. According to our statistics, Indian stock markets experience significant unidirectional volatility spillovers from the US. Over 10-period horizons, S&P 500 shocks account for around 14% of the variation in the NIFTY 50 returns. The research reveals several extremely crucial statistical trends. Gaussian models are insufficient for non-normal distributions with obvious fat tails; hence, robust GARCH-family models are required. Market volatility persistence differs significantly: NIFTY 50 shows strong persistence ($\alpha+\beta=1.072$) approaching non-stationary behavior, whereas S&P 500 shows moderate persistence ($\alpha+\beta=0.534$) with faster mean reversion. Significant both financially and statistically, leverage effects find a 23% rise in S&P 500 volatility responses to negative shocks and a 3.3% rise in NIFTY 50 responses. Importantly, while second-moment transmission is strong (FEVD indicates a 14% variance share), return-level Granger causality is weak (consistent with market efficiency). In risk management, investors have to think about dynamic volatility links, but they can't make money from return causality, so this difference matters. While normal times show an average of 0.018 in dynamic conditional correlations, stress conditions lead to a jump to 0.198. Correlation breakdown is the name of this phenomenon whereby the advantages of diversity disappear precisely when they are most required. These figures suggest that investors face several policy consequences. In normal market conditions, worldwide diversification provides real risk-reduction benefits; yet, during crises when correlations soar, it gives false reassurance. Dynamic rebalancing strategies that change portfolio weights in response to increasing correlations could better manage tail risks than fixed allocation methods.

Second, investors who are very exposed to emerging markets especially those with significant holdings should seriously think about hedging since the 14% variation contribution from US shocks to NIFTY 50 calls is very high. Third, NIFTY 50's high volatility persistence calls for longer-duration hedges than those used for US equities. Studies reveal for legislators and regulators transmission channels via which advanced economy monetary policy affects emerging country stability. Through direct equity volatility transmission, currency appreciation pressures, and capital flow adjustments, Federal Reserve policy normalization causes volatility spillovers to Indian markets via a number of channels. The Reserve Bank of India needs to monitor US volatility spill-overs as a means of financial stability. Rising correlation under stressful times when countercyclically applied capital requirements are necessary should be considered in macroprudential regulations.

The technique created here using dynamic correlation models, many GARCH models capturing both symmetric and asymmetric effects, and VAR causality analysis provides a replicable framework for examining volatility spillovers in other developing market pairs and across several asset classes. Future research should broaden this framework to cover a number of financial cycles, look at sectorial spillovers to grasp several industry effects, and see if spillover patterns change between regular and crisis circumstances. In general, this study expands the body of knowledge on emerging market finance by showing that volatility spillovers are real, have a quantifiable economic effect, and are clearly greater than return spillovers. First, legislators addressing financial stability issues in connected international markets and foreign investors seeking diversification benefits must grasp these mechanisms.

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