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Asymmetric Volatility Transmission And Risk Spillovers Between The U.S. And The Indian Stock Market: Evidence From 2015–2025

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Abstract:
Background: *Stock markets around the world are linked, and shocks from the U.S. market and global fear often reach emerging markets like India, but it remains unclear whether these spillovers behave symmetrically or whether bad news hits harder than good news in recent years.*
Materials and Methods: *This study analyses daily data from 1 April 2015 to 31 March 2025 for the S&P 500 , BSE Sensex 30 and CBOE VIX. It uses regression, TGARCH to capture asymmetric volatility, VAR to study return linkages, Granger causality tests, Impulse Response Functions and Forecast Error Variance Decomposition to measure how shocks move between markets and how long they last.*
Results: *The TGARCH model confirms that volatility is asymmetric, negative shocks push Indian market volatility up more than positive shocks of the same size. Both lagged S&P 500 and VIX movements significantly affect Sensex returns and volatility. VAR, Granger causality, IRFs and FEVD all reveal strong one-way spillovers from the U.S. and the VIX into the Sensex. The S&P 500 drives most of the cross-market action, while the Sensex barely influences the U.S. market.*
Conclusion: *The Indian stock market absorbs return and volatility shocks from global markets, especially the U.S. and the VIX, and reacts more sharply to bad news. Risk management and policy in India must recognise and respond to these external pressures.*
Key Word: *Asymmetric Volatility; Volatility Transmission; Return Spillover; TGARCH; VAR; Impulse Response Function; Forecast Error Variance Decomposition; Granger Causality; CBOE VIX; S&P 500; BSE Sensex; Emerging Markets.*

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I. Introduction

Global stock markets have become tightly interconnected. When the United States market jumps or crashes, the rest of the world reacts, sometimes immediately, sometimes with a delay, and often with an intensity that depends on whether the shock is good or bad. Prior studies show that global equity markets have become increasingly connected, with the United States playing a central role in transmitting shocks to emerging markets.[1] India, as one of the largest emerging markets, is closely tied to these global cycles, especially those driven by the S&P 500 and broader risk sentiment captured by the CBOE Volatility Index (VIX).[3]

In practical terms, investors in India are exposed not only to domestic news but also to external shocks that cross borders through expectations, risk appetite and capital flows. Some of these shocks affect returns directly, while others accumulate in the form of rising volatility. Volatility itself is not symmetric, markets tend to react more forcefully to bad news than to good news of the same size. This asymmetric behaviour is well documented in emerging markets and is precisely why models such as TGARCH are suitable for examining how fear spreads across countries.[6,17]

Over the past decade, the links between the United States and India have strengthened further. Episodes such as the COVID-19 collapse and the post-pandemic waves of volatility have repeatedly shown how quickly movements in the United States spill over into India.[21] Yet, despite this growing integration, spillovers are not balanced. Most studies find that the United States influences India far more than India influences the United States.[8,18] Understanding these patterns matters for anyone managing risk, forecasting returns or designing policy in an interconnected world.

This study examines these dynamics using a combination of asymmetric volatility modelling (TGARCH) and return-spillover frameworks (VAR, Granger causality, impulse response functions and forecast error variance decomposition). Using ten years of daily data for the S&P 500, the Sensex and the CBOE VIX, it addresses one key question: how do United States market movements and global uncertainty affect Indian stock market returns and volatility, and do negative shocks hurt more than positive ones?

Research Problem

Global markets are increasingly interconnected, but the nature of spillovers is not uniform. Most existing studies examine either return spillovers or volatility spillovers, and many ignore the role of asymmetric shocks. This research addresses a clear problem: there is limited recent evidence on how asymmetric volatility and return spillovers travel from the United States market and the VIX to the Indian stock market, and whether these shocks are essentially one-directional.

Need for the Study

This study is necessary for four reasons:

1. Global integration has increased, especially after 2015, making spillovers stronger and more immediate.
2. Post-pandemic volatility has changed how markets react, increasing the importance of models that capture asymmetry.
3. Many studies ignore the role of asymmetric shocks or the influence of the VIX.
4. Investors and policymakers in India need up-to-date evidence on how external shocks influence market stability today.

Objectives of the Study

1. Analyse asymmetric volatility transmission from the United States (S&P 500) to India (Sensex).
2. Examine return spillovers between the markets.
3. Evaluate the role of the VIX as a volatility amplifier in the India–United States system.
4. Study short-run dynamic responses through impulse response functions.
5. Quantify the contribution of each market's shocks using forecast error variance decomposition.

Hypotheses

H1: There is a significant return spillover from the S&P 500 to the Sensex.
H2: Negative shocks have a larger effect on Sensex volatility than positive shocks.
H3: The VIX significantly influences Sensex volatility.
H4: The Sensex does not exert meaningful spillover effects on the S&P 500.
H5: Spillovers between the United States and India are asymmetric and primarily one-directional.

II. Review Of Literature

Early GARCH work on the United States and Indian stock markets shows that volatility shocks in the United States spill into India, especially during periods of global stress, and that the direction is largely one-way.[11,8] Later studies using BEKK and DCC-GARCH on Asian and wider international markets find time-varying correlations and stronger spillovers from the United States into India and other emerging markets when volatility is high.[4,7,9,10,16,18,21] Overall, the United States behaves as a source of shocks, while India mostly absorbs them.[11]

Several papers look at how markets react differently to good and bad news. They consistently find a "bad-news" effect: negative shocks trigger much larger jumps in volatility than positive shocks of the same size.[15,17] For India and other Asian markets this pattern is clear, and asymmetric specifications such as TGARCH and EGARCH outperform symmetric GARCH models in capturing volatility clustering and leverage effects.[6,14,15,17,19] This makes asymmetric GARCH family models the suitable choice when studying spillovers.

Other work includes implied volatility. Studies using India VIX and related indices show that spikes in implied volatility raise stock market volatility and help transmit shocks across emerging markets, including India.[3,14,22] When the CBOE VIX is added into the analysis, the conclusion is same: global uncertainty is a major driver of risk in both developed and emerging markets, with episodes such as the COVID-19 shock leading to pronounced volatility transmission into India.[3,13,21]

Short-run dynamics have been examined using VAR, impulse response functions and variance decomposition. These tools show that shocks from major markets hit others within a day or two and then fade, so return spillovers are fast but relatively short-lived, particularly in volatile periods.[4,12] This underlines that both returns and volatility in India are shaped by external linkages, not just domestic factors.

This literature analysis shows that Indian equity volatility is tightly linked to global shocks, that bad news matters more than good news, and that volatility indices play a central role in measuring and transmitting market fear, highlighting the need to model India within a global, shock-driven framework rather than as a closed, domestic market.

Research Gaps

1. Many studies use pre-2020 data and miss post-COVID behaviour and the most recent phase of integration.[4,12,16]

2. Most papers look at either return spillovers or volatility spillovers on their own, instead of modelling both together.[4,7,11]
3. Very few treat the VIX as central to the United States–India linkage, even though volatility indices are standard measures of global risk.[3,13,22]
4. Asymmetric models such as TGARCH are seldom applied directly to spillovers from the United States and the VIX into the Indian stock market.[6,14,17,19]
5. Hardly any studies combine TGARCH, VAR, impulse response functions, forecast error variance decomposition and VIX-based analysis in one framework.[13,14,21]
6. A number of papers focus on Nifty or sectoral indices rather than analysing Sensex spillovers over a full ten-year window.[8,21]

These gaps justify a study that links asymmetric volatility, cross-market return spillovers and VIX-driven risk transmission between the United States and the Indian stock market over 2015–2025.

III. Methodology

This study uses ten years of daily data for the S&P 500 , the BSE Sensex 30 and the CBOE VIX. All series are converted into daily differenced returns (first differences of the index level) because price levels are non-stationary and not suitable for time-series modelling. The Augmented Dickey–Fuller (ADF) test is applied to confirm that the return series are stationary.

Daily closing values are obtained from standard market data sources. The sample runs from 1 April 2015 to 31 March 2025, yielding 2,395 observations for each series after removing holidays and days with missing values. Any obvious data errors or outliers are cross-checked against alternative sources and corrected where necessary.

Variables

The dependent variable is the daily differenced return on the Sensex 30, representing the Indian stock market. The key independent variables are the daily differenced returns on the S&P 500, capturing the United States equity market, and on the CBOE VIX, which proxy global risk and market fear.

Let $R(t)^{SEN}$, $R(t)^{SP}$ and $R(t)^{VIX}$ denote the daily differenced returns on the Sensex 30, S&P 500 and CBOE VIX respectively.

Models Used

1. TGARCH (Threshold GARCH)

TGARCH is used to study asymmetric volatility, testing whether negative shocks create a larger rise in volatility than positive shocks of the same size. The mean equation for $R(t)^{SEN}$ includes $R(t-1)^{SP}$ and $R(t-1)^{VIX}$, but no lagged Sensex term, because the United States market and global volatility can only affect Indian returns with a one-day delay due to the difference in trading hours.

The variance equation includes:

- the ARCH term (immediate impact of past shocks)
- the GARCH term (persistence of volatility)
- the threshold term (difference between good and bad shocks)
- $R(t-1)^{SP}$ and $R(t-1)^{VIX}$ to capture volatility spillovers into the Sensex

Model selection is guided by information criteria. After estimation, ARCH-LM tests on the standardised residuals and correlograms of residuals and squared residuals are used to check that no serial correlation or remaining ARCH effects are left in the data.

2. VAR (Vector Auto-Regression)

VAR is used to study return spillovers. All three return series ($R(t)^{SEN}$, $R(t)^{SP}$ and $R(t)^{VIX}$) are treated as endogenous variables. The lag length is chosen using standard VAR lag-order criteria (Akaike and Schwarz information criteria), which support a VAR(1) specification. Each equation therefore includes one-day lags of all three returns, consistent with the timing assumption that shocks in the United States market and in global volatility become visible in Indian returns on the next trading day rather than on the same day. The stability of the VAR is checked by ensuring that all inverse roots of the characteristic polynomial lie inside the unit circle.

3. Granger Causality

Granger causality tests examine the direction of influence between markets. They test whether past values of one return series help to predict movements in another and are used to identify whether spillovers run one-way or two-way among the Sensex, the S&P 500 and the VIX.

4. Impulse Response Functions (IRF)

Impulse response functions trace how a one-standard-deviation shock in one market affects the others over several days. They show how quickly the Sensex reacts to shocks from the United States and from global uncertainty, and how fast these effects fade.

5. Forecast Error Variance Decomposition (FEVD)

FEVD measures how much of the forecast error variance of each market is explained by its own shocks and how much by shocks coming from the other markets. This helps to identify which market is dominant in the system and the relative importance of the S&P 500 and the VIX in driving Indian returns.

Diagnostic Tests

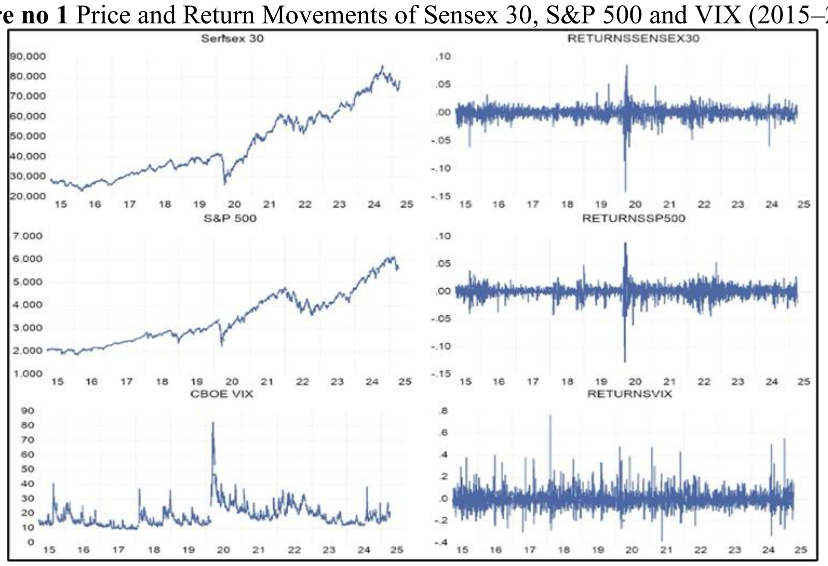
Several diagnostic tests are used to confirm that the models are statistically sound:

- ADF test for stationarity of returns
- ARCH-LM test for volatility clustering
- Serial correlation tests for residual dependence
- Normality tests for residual distributions
- Stability checks for the VAR model

These checks ensure that the modelling framework is appropriate and that the results can be interpreted with confidence.

IV. Results And Discussion

Figure no 1 Price and Return Movements of Sensex 30, S&P 500 and VIX (2015–2025)



The Sensex 30 and S&P 500 both show a steady upward trend over the sample period, confirming that the original price series are non-stationary. When converted to differenced returns, both series fluctuate around a zero mean with no visible trend, indicating stationarity and suitability for time-series modelling.

The VIX index exhibits sudden spikes during periods of heightened uncertainty, especially around major global events and market corrections. When converted to returns, the VIX series also stabilises around a constant mean, consistent with stationarity.

Table no 1 Descriptive Statistics and Normality Test (Jarque-Bera)

Statistic	Sensex Returns	S&P 500 Returns	VIX Returns
Mean	0.00042	0.00042	0.00015
Std. Deviation	0.01017	0.01104	0.08227
Skewness	-1.39	-0.81	1.31
Kurtosis	24.30	18.31	10.92
Jarque-Bera	46031.33	23663.70	6937.78
Probability	0.0000	0.0000	0.0000

The mean daily returns for all three indices are positive but close to zero, indicating the absence of persistent trends over the sample period. The Sensex (–1.39) and S&P 500 (–0.81) show negative skewness, implying that extreme negative returns occur more often than extreme positive ones whereas the VIX (1.31) is positively skewed, consistent with its role as a fear index that spikes during episodes of market stress.

All three series are highly leptokurtic with kurtosis values well above the normal benchmark of 3, confirming fat tails where extreme market movements occur far more frequently than under a normal distribution. The Jarque–Bera statistics reject the null hypothesis of normality at the 5% level (p-value = 0.0000 for all series), so the return distributions are clearly non-normal and asymmetric.

Table no 2 Unit Root Test (Augmented Dickey–Fuller Test)

Index	ADF Test Statistic	5% Critical Value	Prob (F-statistic)	Stationarity
Returnssensex30	-17.661	-2.862	0.0000	Stationary
Returnssp500(–1)	-29.315	-2.862	0.0000	Stationary
Returnsvix(–1)	-52.069	-2.862	0.0000	Stationary

The ADF test statistics for all three indices are much lower than the 5% critical value, leading to rejection of the null hypothesis of a unit root. The F-statistics for all models are significant ($p < 0.05$), confirming that the return series are stationary. This means the mean and variance of each return series remain constant over time.

The findings validate that the use of return data instead of raw prices successfully removes non-stationarity, making these series suitable for econometric and volatility modelling such as GARCH or VAR.

Table no 3 Correlation Analysis

Variables	Sensex Returns	S&P 500 Returns
Sensex Returns	1.000000	0.329767
S&P 500 Returns	0.329767	1.000000

The correlation coefficient of 0.33 between Sensex returns and S&P 500 returns shows a moderate positive relationship, meaning the Indian and U.S. markets often move in the same direction but not perfectly together.

At the same time, the correlation is well below 0.5, so both markets still keep a good amount of independent movement, which makes them useful for diversification.

Table no 4 Regression Analysis

Variable / Statistic	Coefficient	Std. Error	T-Statistic	Prob.
Constant (C)	0.000322	0.000212	1.521877	0.1282
Returnssp500(–1)	0.224871	0.018501	12.15449	0.0000

Model Statistics			
R-squared	0.058214	Adjusted R-squared	0.057820
Durbin–Watson stat	2.2717	Prob (F-statistic)	0.000000

The regression uses Sensex returns as the dependent variable and lagged S&P 500 returns as the independent variable. The F-statistic has a p-value below 0.05, so the model is statistically significant overall. The R^2 of 0.058 means that about 5.8% of the day-to-day movement in Sensex returns is explained by S&P 500 returns from the previous day, which is a small but non-zero effect.

The constant term is not significant ($p > 0.05$), so the average daily return is not different from zero. The coefficient on lagged S&P 500 returns is positive (0.225) and significant ($p < 0.05$), which means that a 1% increase in the S&P 500 return yesterday is associated with about a 0.225% increase in the Sensex return today.

This confirms a short-run positive transmission from the U.S. to the Indian market. The Durbin–Watson value of 2.27 lies in the no serious autocorrelation range.

Regression diagnostics show a mixed picture. The Breusch–Pagan–Godfrey test has a p-value above 0.05, so there is no sign of heteroskedasticity and the residual variance looks constant. The centred VIF of 1 rule out multicollinearity. However, the Ramsey RESET test points to possible non-linearity, and the Breusch–Godfrey LM test detects autocorrelation in the residuals, while the Jarque–Bera test confirms non-normal errors.

Overall, the regression shows a statistically significant but small effect of U.S. returns on Sensex returns. However, the low R^2 and the problems with autocorrelation and non-linearity mean that this simple OLS model is not enough to describe return spillovers, so more advanced time-series models are needed.

Table no 5 Test for ARCH Effects (Engle's LM Test)

Statistic	Statistic Value	P-Value	Conclusion
F-Statistic	85.891	0.0000	ARCH Effect Present
Chi-Square	82.981	0.0000	ARCH Effect Present

The ARCH test checks whether the return series has time-varying volatility. The null hypothesis is that there are no ARCH effects.

Because the p-value of the F-statistic is 0.0000, which is below 0.05, the null is rejected and the series is found to have strong ARCH effects. This means volatility changes over time and tends to come in clusters. The presence of ARCH effects gives a clear reason to use GARCH-type models to study volatility in the later sections.

Table no 6 Threshold GARCH

Component	Coefficient	Std. Error	Z-Statistic	P-Value
Mean Equation				
C	0.000363	0.000161	2.2636	0.0236
Returnssp500(–1)	0.005881	0.003713	1.5828	0.1135
Returnsvix(–1)	–0.008651	0.003272	–2.6444	0.0082
AR(1)	–0.001157	0.001260	–0.9180	0.3586
Variance Equation				
α (RESID(–1)²)	2.81E–06	4.25E–07	6.6409	0.0000
γ (RESID(–1)² × D)	0.019347	0.002497	7.6883	0.0000
β (GARCH(–1))	0.878282	0.007301	120.278	0.0000
Returnsvix(–1)	7.72E–05	3.14E–05	2.4531	0.0142
Returnssp500(–1)	0.012569	0.005408	2.3235	0.0201

Model Statistics			
R-squared	0.0502	Adj R-squared	0.0489
Log Likelihood	8314.683	Durbin-Watson	2.2867

The TGARCH model is estimated with P = 1 and Q = 2, using Sensex returns as the dependent variable, and including lagged S&P 500 returns and lagged VIX returns in both the mean and variance equations.

In the mean equation, the constant term is positive and significant, so the Sensex has a very small but positive average daily return. The lagged S&P 500 return is not significant, which means yesterday's U.S. return does not directly move today's Sensex return once volatility and VIX are included. By contrast, the lagged VIX return is negative and significant, showing that higher global uncertainty tends to push Sensex returns down on the next day.

In the variance equation, the ARCH term is significant, so shocks from the previous day immediately raise volatility. The GARCH term is also significant and close to one, which means volatility stays high for several days before coming back to normal. The threshold term is positive and strongly significant, confirming asymmetric volatility: bad news increases volatility more than good news of the same size. Lagged S&P 500 and VIX returns are both significant in the variance equation, so moves in the U.S. market and changes in global fear mainly affect India through volatility rather than through the mean return.

Overall, the TGARCH model shows that volatility jumps quickly after shocks, remains high for some time, and reacts more strongly to negative shocks. It also shows that volatility spillovers from the U.S. market and from the VIX are present, and that the Indian market gives an asymmetric response to global shocks.

TGARCH diagnostic tests suggest that the model is well specified. The ARCH–LM test on the residuals has a p-value above 0.05, so there are no remaining ARCH effects and volatility clustering has been captured. Correlograms of standardised residuals and of squared residuals show no meaningful autocorrelation and Q-statistic p-values stay above 0.05 across lags, which means there are no leftover patterns in the mean or in the variance.

Because there is no remaining ARCH effect or serial correlation in the residuals, the volatility dynamics appear to be modelled correctly. This gives confidence that the TGARCH results on asymmetric volatility and on the impact of the U.S. market and the VIX can be used reliably to discuss spillovers and risk transmission.

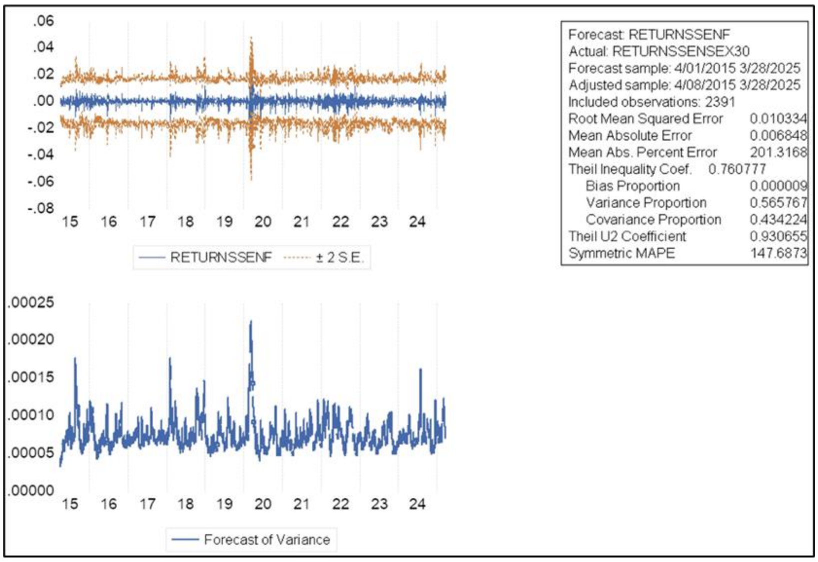


Figure no 2 *Sensex Returns and Variance (2015–2025)*

Figure 2 shows Sensex daily returns and the conditional variance estimated by the TGARCH model. In the top panel, most returns lie inside the ±2 standard-error bands, which means the model tracks the movements in returns without producing extreme or unstable fitted values.

In the bottom panel, the fitted conditional variance rises and falls in clear clusters, with a strong spike around 2019–2020 during the Covid period, when uncertainty in global and Indian markets was very high. These plots show that the TGARCH model captures both the day-to-day behaviour of returns and the way volatility increases in stressful periods and falls back in calmer times.

Table no 7 Vector Auto-Regression (VAR)

Dependent Variable: Returnssensex30	**Coefficient**	**Std. Error**	**t-Statistic**	**P-Value**
Returnssensex30(–1)	–0.020601	0.009806	–2.101927	0.0356
Returnssp500(–1)	0.003086	0.000492	6.278081	0.0000
Returnsvix(–1)	–0.009523	0.003415	–2.787149	0.0053
C	0.000256	0.000168	1.523413	0.1279
Dependent Variable: Returnssp500	**Coefficient**	**Std. Error**	**t-Statistic**	**P-Value**
Returnssensex30(–1)	–0.000285	0.000669	–0.426177	0.6702
Returnssp500(–1)	–0.034099	0.007024	–4.854507	0.0000
Returnsvix(–1)	0.005139	0.002447	2.101632	0.0357
C	0.000800	0.000120	6.637337	0.0000
Dependent Variable: Returnsvix	**Coefficient**	**Std. Error**	**t-Statistic**	**P-Value**
Returnssensex30(–1)	0.032665	0.010137	3.221251	0.0013
Returnssp500(–1)	0.095429	0.018658	5.115692	0.0000
Returnsvix(–1)	0.311454	0.030958	10.05835	0.0000
C	0.003521	0.000730	4.823112	0.0000

Before estimating the VAR model, the ADF test was used to check whether Sensex returns, S&P 500 returns and VIX returns were stationary. All three series are stationary at level ($p < 0.05$), so the VAR can be estimated without further differencing. The three endogenous variables in the system are returnssensex30, returnssp500 and returnvix. Based on the VAR lag-order selection criteria, the optimal lag length is 1, so a VAR(1) model is used.

Table 7 reports the VAR(1) estimates. In the Sensex equation, the coefficient on lagged S&P 500 returns is positive and highly significant, and the coefficient on lagged VIX returns is negative and significant. This means that a rise in U.S. returns tends to increase Sensex returns the next day, while an increase in global uncertainty, captured by the VIX, tends to reduce them.

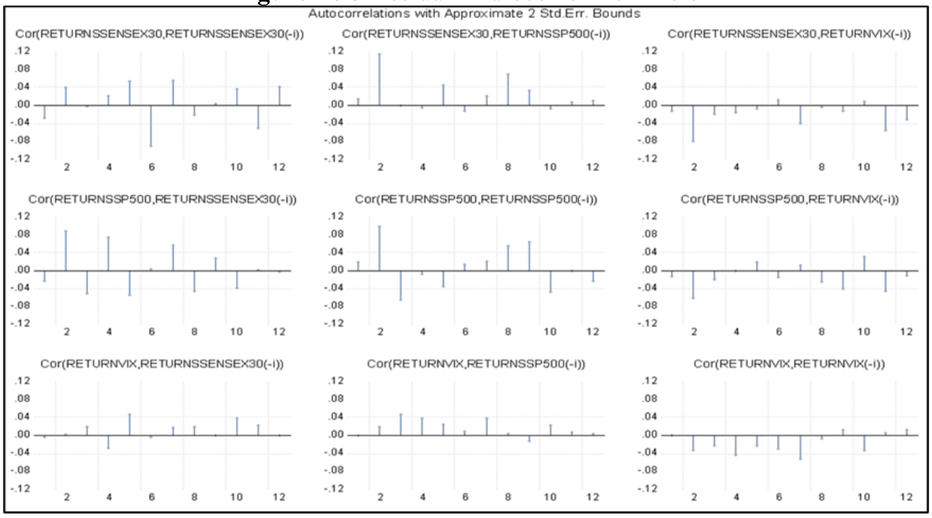
In the S&P 500 and VIX equations, the lagged Sensex return is small and not significant, so past moves in the Indian market do not affect the U.S. market or the VIX in any effective way. In contrast, the lagged S&P 500 and VIX returns are significant in their own equations and in the VIX equation, which means U.S. returns and global fear drive most of the system.

Overall, the VAR results give three clear messages. First, the S&P 500 is the main driver, because its lagged returns push both the Sensex and the VIX. Second, the VIX spreads risk through the system, as changes in global fear quickly show up in U.S. and Indian returns. Third, the Sensex mostly reacts to these outside shocks and does not send important return or volatility effects back to the U.S. market or to the VIX.

VAR model diagnostics

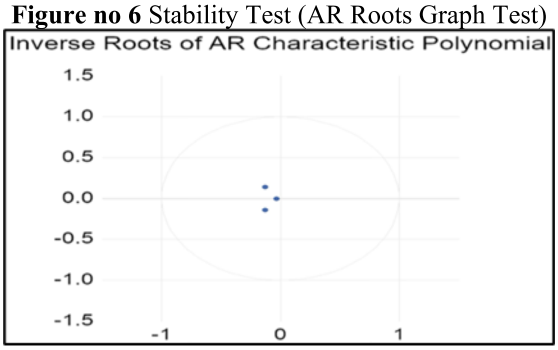
- White heteroskedasticity test: The joint p-value is 0.0000, which shows heteroskedastic residuals. This just means volatility is uneven over time, which is normal for daily stock-return data.

Figure no 5 Residual Autocorrelation Plots



- Residual autocorrelation plots: In the correlograms, the bars for Sensex returns, S&P 500 returns and VIX returns mostly stay within the ±0.12 bands across lags. This supports the view that autocorrelation is weak and the VAR model is acceptable.
- Serial correlation LM test: The test shows only a small amount of autocorrelation in the residuals, not large enough to threaten the model's stability or basic reliability.

Figure no 6 Stability Test (AR Roots Graph Test)



- Stability (AR roots): All inverse roots lie inside the unit circle, so the VAR(1) model is stable and the basic structure is valid.
- Residual normality test: The p-values for skewness, kurtosis and the Jarque–Bera statistic are all 0.0000, so the residuals are not normally distributed.

Overall, the diagnostics show that the VAR(1) model is stable and suitable for studying return spillovers. The heteroskedasticity and non-normality results are common in financial data and do not stop the model from capturing return dynamics, while any remaining serial correlation is small and does not affect overall stability.

Table no 8 Granger Causality Test

Dependent Variable	Excluded Variable	Prob.	Interpretation
Returnssensex30	Returnssp500	0.0000	S&P500 Granger-causes Sensex
	Returnsvix	0.0344	VIX Granger-causes Sensex
Returnssp500	Returnssensex30	0.0069	Sensex Granger-causes S&P500
	Returnsvix	0.0000	VIX Granger-causes S&P500
Returnsvix	Returnssensex30	0.4334	Sensex does not Granger-cause VIX
	Returnssp500	0.0003	S&P500 Granger-causes VIX

Lagged S&P 500 returns strongly help to predict Sensex returns and VIX returns also help to predict Sensex movements, although with a smaller effect. Lagged Sensex returns have a statistically significant but very small effect on S&P 500 returns, so India's impact on the U.S. market is negligible in practice. For the VIX equation, Sensex returns do not help at all, while S&P 500 returns clearly do. This pattern fits the idea that U.S. market moves and global fear drive the system, and the Indian market mainly reacts to them.

Figure no 7 Impulse Response Functions (IRFs)

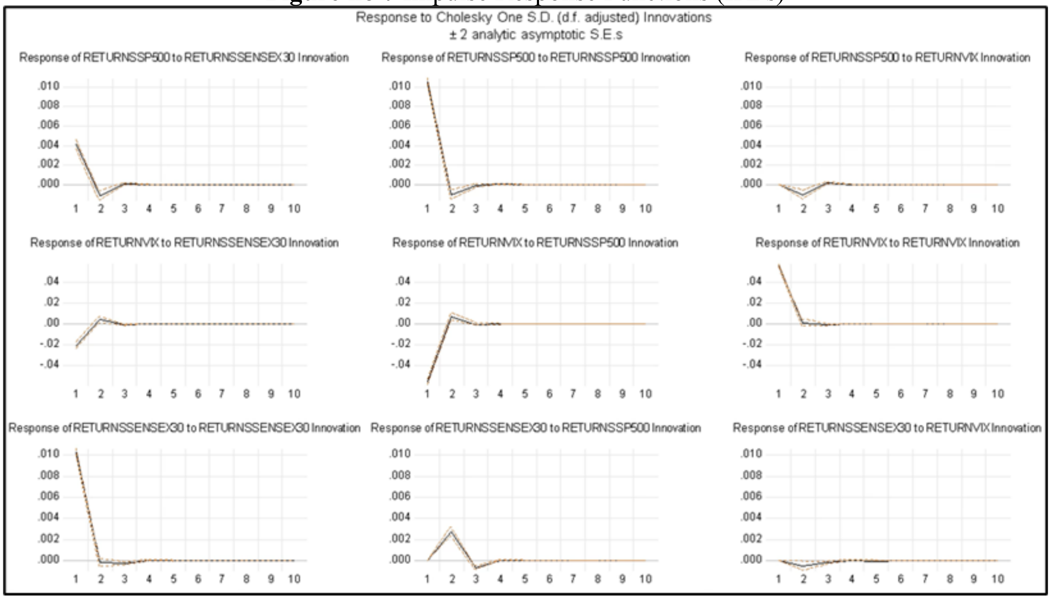


Figure 7 shows how each market reacts when one variable gets a one-day shock. A shock to the S&P 500 leads to an immediate response in the Sensex on the next day and the effect almost disappears within two to three days. A VIX shock makes the Sensex move sharply in the opposite direction on Day 1, which shows that higher global fear quickly pushes Indian returns down.

Shocks that start in the Sensex hardly affect the S&P 500 or the VIX, because their IRF lines stay close to zero. This means India does not send any meaningful return or volatility spillovers back to the U.S. market. The link between the S&P 500 and the VIX is strong in both directions: a VIX shock pushes the S&P 500 down, and S&P 500 shock slightly lowers the VIX, showing that market moves and global risk sentiment influence each other both ways. Overall, the IRFs make it clear that the S&P 500 leads and the Sensex mostly reacts.

Table no 9 Forecast Error Variance Decomposition (FEVD)

Variable (Period 10 Values)	From Sensex (%)	From S&P 500 (%)	From VIX (%)
Sensex	92.73	7.07	0.20
S&P 500	85.34	13.88	0.78
VIX	47.02	46.58	6.40

The FEVD results show how much of each market's movement is driven by its own shocks and how much comes from the others. The S&P 500 is mostly self-driven, with more than 85 percent of its variance explained by its own shocks after ten periods, the Sensex adds around 14 percent and the VIX almost nothing. This means the U.S. market is influenced only slightly by India and global volatility.

The VIX has a more balanced pattern: about half of its variance comes from its own shocks and about half from the S&P 500, while the Sensex again plays a very small role. For the Sensex, more than 92 percent of its variance comes from its own shocks, with roughly 7 percent from the S&P 500 and less than 1 percent from the VIX. So the Indian market is mainly driven by domestic factors but still responds to U.S. moves, although the effect is limited.

Overall, these FEVD results line up with the VAR, OLS and Granger causality findings: shocks mainly flow from the U.S. market and the VIX towards India, while feedback from the Sensex to the U.S. market and the VIX is small and not economically important.

V. Outcomes From This Research

1. The S&P 500 consistently appears as the main driver in the system. When the U.S. market moves, the Sensex usually reacts the very next day. This supports H1, which states that there is a significant return spillover from the S&P 500 to the Sensex.
2. The VIX acts as a volatility amplifier. A spike in the VIX pulls down Sensex returns and pushes volatility higher, confirming H3 that the VIX significantly influences Sensex volatility.
3. India reacts more aggressively to bad news than to good news. A negative shock creates a bigger jump in volatility than a positive shock of the same size, which confirms H2 about asymmetric volatility in the Sensex.
4. The Sensex has only a very small influence on the U.S. market. Spillovers run mainly from the U.S. and the VIX to India, with feedback from the Sensex to the S&P 500 and the VIX being limited and not economically important. This supports H4 and H5, which state that the Sensex does not exert meaningful spillover effects on the S&P 500 and that spillovers are mostly one-directional.
5. The impulse response functions show that the Sensex reacts immediately to shocks from the S&P 500 and the VIX, and the effects fade within two to three days but the initial reaction is sharp.
6. The FEVD results show that the S&P 500 explains most of its own movements and a sizeable share of VIX movements while the Sensex remains mostly self-driven but still influenced by U.S. shocks. This confirms that the U.S. market and global fear indices dominate the system, while India mainly adjusts to their shocks.

VI. Practical Implications

Implications for Investors

- Expect sharper reactions to negative news. Because volatility is asymmetric.
- Short-term trading must factor in global sentiment because the Sensex reacts strongly to S&P 500 and VIX shocks and the effect fades within two to three days.
- Watch the U.S. market and the VIX before looking at India; large moves there usually show up in Indian returns and volatility on the next day.

Implications for Policymakers

- Global shocks enter India quickly, so regulation and policy need to account for this external dependence.
- Even when Indian fundamentals are strong, global risk-off events can still hurt the market, so policies should recognise this vulnerability.
- Since most spillovers come through global sentiment and U.S. price movements, real-time tracking of foreign flows and the VIX is essential.
- Stress tests should build in asymmetric behaviour, because traditional symmetric models underestimate the impact of negative shocks.

Implications for Portfolio Managers

- Hedging strategies should include VIX-linked instruments, because the VIX amplifies volatility spillovers and ignoring it weakens risk control.
- Cross-market models should treat the U.S. as the lead market, since S&P 500 movements consistently drive returns and volatility in India.
- Expect fast adjustments and short-lived spillovers (most responses die out within a couple of days), so short-term allocation and rebalancing should use this horizon.
- Build portfolios assuming downside reactions will be stronger than upside moves, and set position sizes and stop losses to reflect this.

VII. Limitation Of The Study

1. Single volatility model: The study uses only one asymmetric model (TGARCH) to capture volatility transmission. Other models such as EGARCH, BEKK or DCC-GARCH might pick up different forms of spillovers or changing correlations that this model misses.
2. Narrow set of variables: Only three series are included: the Sensex, the S&P 500 and the VIX. Other important global indices, sector indices and macro factors (interest rates, exchange rates, inflation, policy uncertainty) are not modelled, so the system is a simplified view of reality.
3. Linear VAR for returns: The VAR model is linear and uses one fixed lag, so it cannot fully capture more complex behaviour such as non-linear effects, crisis regimes or spillovers that change over time.
4. Daily frequency only: The analysis relies on daily closing data. Intraday shocks and high-frequency spillovers are ignored, so very fast reactions within the trading day are not observed.

5. The residuals of the VAR model are heteroskedastic and not normally distributed. This is common with financial data, but it means some standard assumptions are not met. Because of this, the test results can be less precise, and more flexible models might be needed for better accuracy.
6. Sample window and stability: Results are based on the 2015–2025 period, which includes COVID-19 and other specific events. If the behaviour of markets changes in the future, the size and direction of spillovers found here may not hold.

VIII. Future Scope

1. Future work can use high-frequency data (hourly or intraday) to capture very fast spillovers that daily data cannot show, especially around announcements and crisis days.
2. More advanced volatility models such as EGARCH, BEKK or DCC-GARCH can be applied to study changing correlations and richer volatility spillovers between the S&P 500, the Sensex and the VIX.
3. The analysis can be extended to a wider set of markets by adding other major indices like NASDAQ and Dow Jones, as well as key Asian and European indices, to map a full global spillover network.
4. Adding macroeconomic variables (policy rates, inflation, exchange rates, oil prices, policy-uncertainty indices) would help connect return and volatility spillovers to underlying economic shocks rather than only to price movements.
5. Non-linear and time-varying models such as Markov-switching VAR, time-varying parameter VAR models, could be used to capture regime shifts and changing spillover strength between calm and crisis periods.
6. Future studies can also focus on sector-level or factor-based indices within India (for example, banks, IT, energy) to see which sectors are most sensitive to U.S. market moves and spikes in global fear.
7. Researchers can revisit the same framework in later years or during future crises to check whether the direction and size of spillovers remain the same or whether India's role in global markets becomes stronger over time.

IX. Conclusion

This study shows that the Indian stock market is closely linked to what happens in the United States. When the S&P 500 moves, the Sensex usually reacts the next day, so the U.S. market leads and India follows. Putting it all together, the results show that Indian market behaviour is shaped mainly by global conditions, especially U.S. market movements and changes in global uncertainty captured by the VIX . Anyone trying to understand or predict the Sensex must pay close attention to U.S. developments and to the signals sent by the VIX.

By highlighting these patterns, the study provides a base for future research and offers practical insights to help investors, policymakers and market participants think more clearly about cross-market linkages.

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