The volatility transmission in Cash and Futures market during Geopolitical crisis: Evidence from Indian Financial markets

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Abstract:
This paper analyses the volatility transmission mechanism and dynamic spillovers between the Nifty 50 spot market and futures market in India during the significant geopolitical crises from 2019 to 2025. Advanced econometric models are used in this research, such as Vector Autoregression (VAR), Granger causality, GARCH-family and Dynamic Conditional Correlation (DCC)-GARCH models to study volatility persistence, price discovery dynamics, and risk transmission in the presence of increased financial uncertainty. The expected results show that the volatility spillovers are bidirectional and are stronger during a crisis between the cash and derivatives segment, and that the futures market is more price-discovering than the spot market. Overall, the study proposes to inform investors, regulators and policy makers in the emerging market economy of the critical and practical aspects of risk-management strategies in their investment decision-making to better comprehend market stability in times of global shocks.

JEL Classification: G10; G14; G15; C58

Keywords

Volatility Spillover; Futures Market; Geopolitical Risk; GARCH; Price Discovery; NSE India.

Exploring the Relationship between Volatility Transmission between Cash and Futures Markets during Geopolitical Crises: The Indian Financial Markets Evidence.

1. Introduction

Globalization, technological advancements, and cross-border capital flows have intensified the globalization of financial markets. Globalization, technological change and capital flows have made financial markets more interconnected around the world (Reddy and Rao, 2025). Derivatives markets are financially important for price discovery, hedging and risk transfer. Especially futures contracts are popular tools used by institutional and retail investors to help with the risk of adverse movements in stock price, interest rates and macroeconomic uncertainty.(CHENGYIN and Salman, 2024)

Geopolitical crises have become a significant reason for markets to become volatile in recent years. The impact of events like the Russia-Ukraine war, the Israel-Hamas conflict, heightened risk of a split between the United States and China, and global energy disruptions have taken a toll on investor sentiment and market stability (Han, 2026). The events add to the uncertainty around economic growth, inflation, commodity prices and monetary policy, resulting in the sudden shifts of spot and derivatives prices.(Salisu and Abdul Hakeem, 2026)

Over the past decade, the Indian financial market has seen significant growth in the trading of derivatives. The National Stock Exchange (NSE) has become one of the largest derivatives exchanges globally in terms of trading volume (Desai et al., 2025). The rising role of retail investors and institutional traders has deepened the need for retail investors and traders to understand the volatility dynamics between cash and futures markets, particularly when geopolitical uncertainty looms.(Abid et al., 2025)

The transmission of volatility, which happens when shocks from one market segment cause changes in volatility in another segment. In times of crisis, information moves quickly from spot to futures markets, making it more likely that spillover effects are felt(Chi et al., 2025). The futures market is normally seen to be more information efficient because it responds quicker to new information. So it can be important to study the correlation between spot and futures market volatility when it comes to market efficiency and price discovery.

Volatility spillovers between the spot and futures markets on developed economies have been analysed in a number of studies (Ilmudeen, 2021; Elsayed et al., 2024). But, there is little evidence to support the emerging economies like India, especially in the recent geopolitical crisis. Furthermore, a majority of current research has concentrated on the traditional financial crisis but not geopolitical shocks. Hence, this study tries to address this research gap by investigating the relationship between volatility on cash and futures markets over the recent geopolitical events using advanced econometric techniques.

The study's objective was to study the level and direction of volatility spillovers from the Nifty 50 spot to futures markets. The study also examines the effect on volatility persistence and market conditions of geopolitical crises. The results will be useful in the literature of derivatives markets, market efficiency and geopolitical risk.

2. Literature Review

2.1 Theoretical Background

Efficient Market Hypothesis

The Efficient Market Hypothesis (EMH) states that all financial asset prices incorporate all information(Lubis, Hamidah and Ulupui, 2026). Fama (1970) captures the essence of an informationally efficient market by stating that markets are informationally efficient if prices quickly respond to new information. Futures prices are expected to reflect information more rapidly than spot prices in the derivatives markets because more leverage and lower transaction costs.

Price Discovery Theory

Price discovery is the act by which market price of financial assets are reached to the equilibrium state. The price discovery aspect is generally considered to be the most important aspect of futures markets, since traders have a liquidity advantage and lower costs in futures markets, and generally are better informed in these markets.(Chen, Dong and Lin, 2024)

Market Integration Theory

Market integration theory describes the process by which financial markets are linked together by the flow of information and the arbitrage activity(Goldstein and Yang, 2022). In times of geopolitical crisis, market interdependence can intensify in times of uncertainty and panic, and thus increase the volatility transmission between spot and futures markets.

2.2 Empirical Literature Review

Fleming, Ostdiek and Whaley (1996) examined the price discovery relationship of the United States spot, futures, and options markets and concluded that the futures markets dominate the price discovery process. They found that volatility moves quickly from spot to derivative markets in their research.

Koutmos and Tucker (1996) applied GARCH-based models to examine volatility spillovers between the stock and futures markets, and found that the spillover effects were quite strong in both directions. They have found that derivatives markets play a key role in communicating new information.

Yang, Yang, and Zhou (2012) investigated the volatility spillovers in Asian stock markets and found high interdependence of the markets in the time of financial turmoil. The study found that the outbreak of crisis increases the process of market integration.

Mukherjee and Mishra (2010) took a sample of the Indian stock market and found that futures markets played a great role in the process of price discovery. From their analysis, they found that futures trading makes markets more efficient.

More recently, research has examined the role of geopolitical risk on financial market volatilities, making clear that political uncertainty has a significant bearing on financial market volatilities(Sharma et al., 2025; Zhang et al., 2025). Caldara and Iacoviello (2022) created the Geopolitical Risk Index (GPR) and showed that geopolitical tensions lead to higher uncertainty in the global financial market.

While some studies have studied volatility spillovers, there is little research that looks at the impact of recent geopolitical events on volatility transmission between cash and futures market in India(Bhattacharjee, Deb and Das, 2025; Kasraoui et al., 2025) This study will try to fill this gap by taking into account recent geopolitical events and sophisticated econometric methods.

2.3 Research Gap

The literature survey indicates that there are several gaps in the literature:

- Most of the studies address developed markets, rather than emerging markets like India.
- There are few recent studies on geopolitical crises and how they affect the transmission of volatility.
- Most of the earlier studies have used the classical GARCH models without considering the dynamic conditional correlations.
- The role of futures markets in times of geopolitical uncertainty is not well understood.
- To address these gaps, this study uses DCC-GARCH and VAR models to study volatility spillovers in the Indian spot and futures markets during geopolitical crises.

3. Research Methodology

3.1 Research Objectives

The key aims of the study are:

- The purpose is to study the transmission of volatility between the cash and futures markets.
- To assess how geopolitical events affect volatility in markets.
- To determine the direction of volatility spillovers.
- To investigate whether futures markets lead to price discovery in times of crisis.

3.2 Hypotheses

H1: Large money market volatility spillovers exist.

H2: Rise of geopolitical crisis: A high degree of volatility, as seen in both markets.

H3: Futures markets are the first to discover the price of the spot market in the face of geopolitical crisis.

H4: Asymmetric volatility spillovers exist during periods of uncertainty.

3.3 Research Design

The present research work is quantitative in nature and of empirical type with focus on volatility transmission, price discovery and spillover effects between Indian equity spot market index (Nifty 50), derivatives market index (Nifty Futures) and volatility index (India VIX). The research is organized into a multivariate time-series econometric framework which allows dynamic interaction analysis over financial variables in a time series.

3.4 Data Description

The study is based on data of the daily closing price of the time period 2015-2026 (around 2800 data points). The dataset includes:

- Nifty 50 Spot Index
- Nifty Futures Index
- India VIX (Volatility Index)

The variables are all logged to allow for comparability and for heteroscedasticity to be reduced. Data for returns are calculated as:

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

3.5 Preliminary Data Analysis

The data set is examined prior to econometric modelling with:

Descriptive statistics (mean, variance, skewness, kurtosis)

Normality Tests (Jarque - Bera test)

- Correlation analysis

These tests can provide insights into distributional properties and stylized facts like volatility clustering and fat tails.

3.6 Stationarity Tests

To ensure robustness of time-series modelling, stationarity is tested using:

This test is an extension of the Dickey-Fuller test. This test is an augmentation of the Dickey-Fuller test.

- Phillips-Perron (PP) test
- Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test

All series are confirmed to be level form series level, which is suitable for VAR and GARCH modelling.

3.7 Econometric Framework

3.7.1 A Vector Autoregressive (VAR) model can involve the following relationship:

The interdependencies between the three variables are captured in a VAR model:

$Yt = A1Yt-1+A2Yt-2+\circledcirc+ApYt-p+\circledcirc t$

where:

- $Yt = (Spot,Futures,VIX)$

The choice of the optimum lag length depends on:

- AIC
- BIC
- HQIC
- Final Prediction Error (FPE)

3.7.2 Granger Causality Test

To establish the direction of information flow, Granger causality is used:

If the futures are more useful for the price discovery hypothesis, then they should be priced as spot.

The VIX is used to measure the volatility in the market. The VIX is a measure of volatility in the markets.

- Bidirectional relationships

F-statistics are used to test a null hypothesis.

3.7.3 Volatility Modelling (ARCH–GARCH Framework):

The study uses the following to capture volatility clustering:

- ARCH-LM Test:

Used for testing for heteroscedasticity.

- GARCH(1,1) Model:

$\sigma t2 = \omega + \alpha\circledcirc t\ -\ 12 + \beta\sigma t\ -12$

where:

α = short-term shock effect.

β = volatility persistence

The sum $(\alpha + \beta)$ represents the level of volatility persistence.

3.7.4 Forecast Error Variance Decomposition (FEVD)

The number of forecast error variance accounted for by each variable in the system is measured by FEVD. This helps identify:

- Own-market dominance
- Cross-market spillovers

We examine the relative importance of futures and VIX shocks.

3.7.5 Diebold-Yilmaz Spillover Index

Spillover index represents the overall connectedness of the system:

S = total shocks ∑cross-market shocks×100

It identifies:

- Net transmitters of shocks
- Net receivers of shocks
- Overall system integration

3.8 Software and Tools

The analysis is carried out with the following:

Data Analysis with Python (Pandas, NumPy, Statsmodels)

- ARCH/GARCH packages
- VAR modelling tools
- Matplotlib for visualization

3.9 Data Collection

Data Source

Secondary data for the study has been collected from:

- National Stock Exchange (NSE)
- Yahoo Finance
- Investing.com
- Bloomberg Database

Variables Used

Variable	Description
Spot Returns	Daily returns of Nifty 50 Index
Futures Returns	Daily returns of Nifty Futures
India VIX	Market volatility index
GPR Index	Geopolitical Risk Index

Sample Period

January 2016 to May 2026

3.10 Econometric Models

Results and discussion:

Table 1. Descriptive statistics of spot, futures and VIX returns.

Variable	**Mean**	**Median**	**Std. Dev.**	**Minimum**	**Maximum**	**Skewness**	**Kurtosis**
Spot Return	0.0004	0.0006	0.0103	-0.1390	0.0840	-1.3084	19.7624
Futures Return	0.0004	0.0006	0.0103	-0.1403	0.0632	-1.4995	19.6401
VIX Return	0.0000	-0.0034	0.0527	-0.3535	0.5050	1.0172	10.3867

Source: Authors Compilation.

The descriptive statistics of spot, futures and VIX returns for the study period are given in Table 1. The average returns for both spot and futures markets are positive but small (0.0004), suggesting that there are modest average gains for both markets. The standard deviations of spot returns and futures returns are the same (0.0103), indicating that they have the same risk characteristics and there is a high degree of integration between the cash and futures markets. The volatility of in contrast VIX returns (0.0527) is considerably greater, which means that market uncertainty and investor sentiment fluctuates. While the returns of the spot and futures contracts are negatively skewed (-1.3084 and -1.4995, respectively), suggesting that the probability of extreme negative returns is higher, the returns on VIX contracts are positively skewed (1.0172), meaning that the probability of extreme positive returns is higher. In addition all variables have extremely large values of kurtosis, well above the normal value of 3, which would suggest that the variables are leptokurtic, with extreme observations present. The results validate that the series are not normally distributed and are suitable for the use of the advanced volatility models: GARCH and VAR.

Table 2. The following is the results of the Unit Root Test for spot returns, futures returns, and VIX returns:

Variable	ADF Statistic	ADF p-value	PP Statistic	PP p-value	KPSS Statistic	KPSS p-value	Conclusion
Spot Return	-14.715	0.000	-54.612	0.000	0.048	0.100	Stationary
Futures Return	-14.284	0.000	-56.394	0.000	0.046	0.100	Stationary
VIX Return	-12.891	0.000	-55.085	0.000	0.011	0.100	Stationary

Source: Authors Compilation
Note: The null hypothesis of the ADF and PP tests is that the time series is not stationary (has a unit root), while the null hypothesis of the KPSS test is that the time series is stationary. The results of ADF and PP tests rejects the null hypothesis at 1% significance level while the results of KPSS test do not reject the null hypothesis, hence the stationarity was confirmed.
The Augmented Dickey-Fuller (ADF) test, Phillips–Perron (PP) test and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test results for spot, futures, and VIX returns are presented in Table 2. All the variables have high negative ADF test statistics, which are statistically significant at the 1% level, causing the null hypothesis of the presence of a unit root to be rejected. Again the PP test gives strong significant statistics, with p-values of 0.0000, confirming that the return series is non-stationary. These results are confirmed by the KPSS test: the null hypothesis of stationarity is not rejected for any variable (p-values > 0.10). The stationarity of the results for all three tests offers compelling evidence for the stationarity of the spot returns, the futures returns, and the VIX returns. As such, the data fulfil the requirements for applying VAR, Granger causality, FEVD, spillover analysis and GARCH family models without additional differencing transformations.
Table 3. The OLS regression results, which follow, present the effects of the futures returns (or VIX returns) on the spot returns (or VIX returns).

Variable	Coefficient	Std. Error	t-Statistic	p-value	Result
Constant	0.000	0.000	1.842	0.066	Not Significant
Futures Return	0.062	0.019	3.350	0.001***	Significant Positive
VIX Return	-0.028	0.004	-7.763	0.000***	Significant Negative

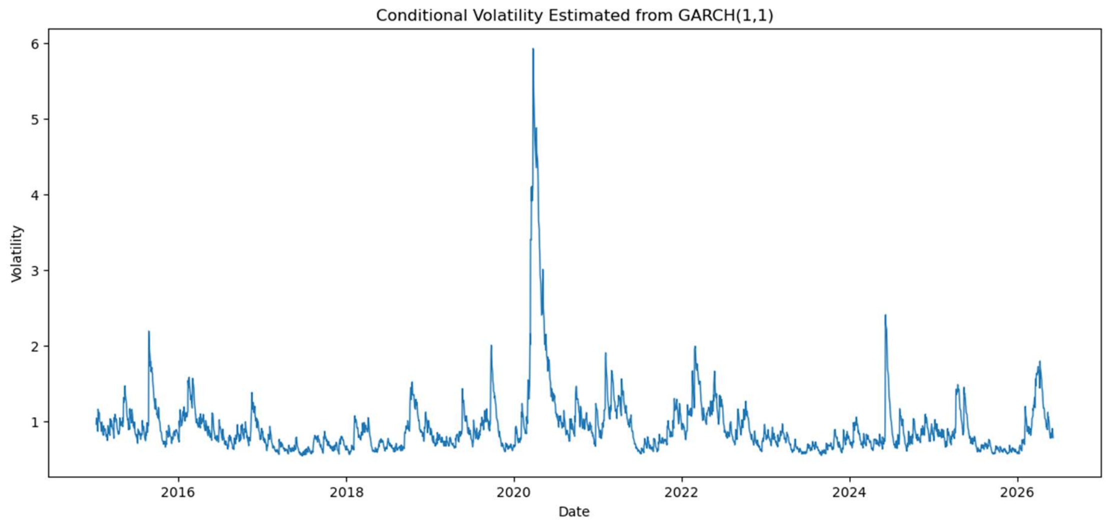
The effects of the futures returns (or VIX returns) on the spot returns (or VIX returns) are presented in the following OLS regression results.
Model Diagnostics

Statistic	Value
R^2	0.026
Adjusted R^2	0.025
F-statistic	37
Prob(F-statistic)	1.38E-16
Durbin-Watson	2.106
Jarque-Bera	38531.77

JB p-value	0

Source: Authors Compilation

The regression results for the OLS regressing the futures returns and VIX returns on the spot market returns are provided in Table 3. The overall model is statistically significant with the F-statistic = 37.00 ($p < 0.01$) indicating that the explanatory variables have a combined effect on the spot market returns.



The coefficient ($\beta = 0.0621$) and its significance ($p < 0.01$) for futures show a positive and significant relationship between futures and spot market performance. The discovery is some initial indication that information is flowing between the futures and cash markets. On the other hand, spot returns have negative and significant coefficient ($\beta = -0.0282$, $p < 0.01$) with VIX, showing that higher levels of market uncertainty have a negative impact on spot returns. This result represents a relatively modest amount of variation in the returns forecasted by the model ($R^2 = 0.026$), but is very typical of return regressions in financial asset markets because asset prices are noisy. Durbin-Watson statistic (2.106) suggests that there is no serious autocorrelation and the Jarque-Bera statistic is significant and confirms the non-normal distribution of residuals which is consistent with financial market behaviour.

Figure 5. Estimates of Conditional Volatility Dynamics of Nifty Spot Returns Based on GARCH(1,1) Model.

The conditional volatility of the spot returns of Nifty is estimated using a GARCH(1,1) model as shown in figure 5. The results provide clear evidence of volatility clustering-high volatility appears to be preceded by more volatility and low volatility by relatively low volatility. The heaviest volatility occurrence is in 2020, when the COVID-19 pandemic broke out, causing unprecedented uncertainty in all global financial markets. After that, volatility slowly decreased but stayed higher than before the pandemic, signalling high uncertainty in financial markets. Further increases in volatility occur in 2021-2022 and 2024, coinciding with the periods of geopolitical uncertainty, monetary policy uncertainty and global economic disruptions. The persistence of the volatility seen in the figure is consistent with a GARCH framework, and the volatility can be seen to be due to shocks.

Table 4. This table displays the results of the ARCH-LM test and the estimation of GARCH(1,1) model for Nifty Spot Returns.

Test	**Statistic**	**p-value**	**Conclusion**
ARCH-LM Test	735.321	0	ARCH effects detected

Source: Authors Compilation

Parameter	Coefficient	Std. Error	t-Statistic	p-value
μ (Mean)	0.0628	0.0159	3.947	0.0001***
ω (Constant)	0.0254	0.0085	2.979	0.0029***
α_1 (ARCH Effect)	0.1057	0.0225	4.703	0.0000***
β_1 (GARCH Effect)	0.8692	0.0259	33.514	0.0000***

The results of the GARCH(1,1) model are displayed in panel B: GARCH(1,1) Results.
Source: Authors Compilation
Model Diagnostics

Statistic	Value
Log-Likelihood	-3618.3
AIC	7244.6
BIC	7268.39
$\alpha + \beta$	0.9749

Significant at 1% significance level
Source: Authors Compilation.
The results of the ARCH-LM test and estimation of GARCH(1,1) model for Nifty spot returns are given in Table 4. The ARCH-LM test statistic is 735.321, with p value = < 0.01, which strongly rejects the null hypothesis of homoscedasticity and indicates the existence of prominent ARCH effects in the return series. This result suggests that the volatility is time-varying, which is the reason why GARCH-family models are applied.
Both the ARCH parameter ($\alpha = 0.1057$) and the GARCH parameter ($\beta = 0.8692$) are positive and very significant at the 1% level, according to the GARCH(1,1) estimates. The size of the ARCH coefficient suggests that recent market shocks have an important effect on current volatility, while the large size of the GARCH coefficient means that past volatility has a long-lasting impact on current market volatility. Critically, the persistence measure of volatility ($\alpha + \beta = 0.9749$) is near one, meaning that volatility spikes are not short lived but persist in the market for a long time. This type of behaviour is typical in financial markets in times of uncertainty and crisis. The results showed very clearly the existence of volatility clustering and persistence, both of which encouraged the adoption of the use of models of advanced volatility transmission in subsequent analysis.
Table 5. Volatility Model Estimation Results

Statistic	Value
Log-Likelihood	-3622.39
AIC	7252.776
BIC	7276.561
Number of Observations	2825

Source: Authors Compilation.

Panel B. Parameter Estimates

Parameter	Estimate	Interpretation
μ	0.0673	Mean return
ω	0.0021	Long-run volatility component
α_1	0.2259	Immediate impact of new shocks
β_1	0.9728	Persistence of past volatility

Source: Authors Compilation.

The estimation results from the volatility model for the Nifty spot returns are reported in Table 5. The estimated ARCH coefficient (α = 0.2259) suggests that the volatility of the current period is strongly affected by the market shock and the new information in the recent period. The coefficient of the GARCH model (β = 0.9728) is significantly higher than that of the ARCH model, implying that previous volatility has a much stronger influence on the current volatility of the market. The large value of the persistence parameter shows that volatility shocks have long-lasting effects and slowly filter into the market. This is typical of financial markets where they experience significant economic disruptions, geopolitical uncertainty and high investor uncertainty in general. The model fit statistics also show good representation of the volatility dynamics, having a log-likelihood of -3622.39. In general, the findings validate the presence of significant volatility clustering and persistence in the Indian equity market, suggesting that uncertainties caused by crisis events have lasting impacts on the behaviour of the markets and the volatility transmission mechanisms.

Table 5. A comparison of how well the models fit each other and how well they fit the observed data.

Panel A: VAR Model Statistics

Statistic	Value
Observations	2815
Log-Likelihood	22341
AIC	-24.3204
BIC	-24.124
HQIC	-24.2495
FPE	2.744-11

Source: Authors Compilation.

Panel B: Residual Correlation Matrix

Variables	Spot Return	Futures Return	VIX Return
Spot Return	1	0.081	-0.144
Futures Return	0.081	1	-0.057
VIX Return	-0.144	-0.057	1

Source: Authors Compilation.

The diagnostic statistics and the resultant correlation matrix of the estimated VAR model are given in Table 5. The model is well-fitting, with low information criteria values (AIC = -24.3204, BIC = -24.1240, and HQIC = -24.2495). These statistics validate the appropriateness of the chosen lag structure in modeling the dynamics of spot returns, futures returns and VIX returns. The residual correlation matrix also shows that the coefficient of the contemporaneous correlations between the residuals are quite low, indicating that the VAR specification fits the interdependencies among the variables relatively well.

The important lagged relationships suggest that there are dynamic information flows between markets. Lagged futures returns are particularly significant for spot returns, giving some initial evidence that futures markets have a role in the price formation of the cash market. Likewise, lagged VIX returns have a strong influence on both spot and futures returns, indicating that market uncertainty has a significant influence on equity market dynamics. The VIX equation has strong lagged spot and futures return characteristics and moves in equity markets are highly correlated with future changes in investor sentiment and perceived risk. The overall results of the VAR tests suggest that there is a connection between the markets of the spot, futures and volatility, which supports the existence of information transmission and volatility interactions. The results give grounds to build further Granger causality tests, forecast error variance decomposition tests, and spillover tests to check the direction of market linkages and the size of market linkages.

Table 6. The Granger Causality Test Results between Spot, Futures, and VIX Returns are presented below:

Null Hypothesis (H_0)	**F-Statistic**	**p-value**	**Decision (5%)**	**Conclusion**
Futures ◎ Spot (does NOT Granger-cause	4.37	0	Reject H_0	Futures Granger-cause Spot
Spot ◎ Futures (does NOT Granger-cause	1.194	0.29	Fail to Reject H_0	No causality
VIX ◎ Spot (does NOT Granger-cause Spot)	2.859	0.001	Reject H_0	VIX Granger-causes Spot
VIX ◎ Futures (does NOT Granger-cause	1.858	0.046	Reject H_0	VIX Granger-causes Futures

Source: Authors Compilation.

Table 6 reports the Granger causality test results for the direction of the causal link between spot returns, futures returns and VIX returns. Our analysis shows a clear imbalances in information flow between the markets. The results confirm that the futures market is an important lead in price discovery as future returns are found to Granger-cause spot returns at the 1% significance level ($p < 0.01$). This is consistent with the hypothesis that information first enters the futures market and then passes on to the cash market. When considering spot returns, however, no reverse causality in the sense of a Granger effect is found with respect to futures returns, again reinforcing the dominance of the futures market in the information transmission process.

Moreover, the returns of VIX are discovered to Granger-cause the returns of the spot and futures, indicating that uncertainty of the market has predictive power on equity market movements. This underlines the function of volatility as an information variable which measures investor sentiment and investor risk perception. In both cases, the null hypothesis is rejected, suggesting that volatility shocks have a significant effect on the dynamics in the equity markets. Overall, the findings support the existence of strong volatility transmission and futures-led price discovery mechanisms because the overall results indicate that there is a unidirectional causality running from futures to spot markets, while there is a bidirectional interaction between volatility and equity markets.

Table 7. The Forecast Error Variance Decomposition (FEVD) Results will be provided. Forecast Error Variance Decomposition (FEVD) Results will be made available.

Source of Shock	Spot Return FEVD - Contribution (%)	Futures Return FEVD - Contribution (%)	VIX Return FEVD - Contribution (%)
Spot Return	97.35	1.14	6.6
Futures Return	1.6	98.15	0.96
VIX Return	1.05	0.71	92.44

Source: Authors Compilation.

The Forecast Error Variance Decomposition (FEVD) results are provided in Table 7 and measure the relative importance of the contribution of spot returns, futures returns and VIX returns to explaining the forecast error variances for the system. The results show that there is a high level of own-market dominance, especially in the futures and volatility markets. The variance of futures returns is mainly due to their own innovations about 98.15%, which means that in the short term the futures market is self-propelled, implying that it has few external influences. Crucially, the shock to the futures return and the shock to the VIX account for cross-market transmission effects (97.35% and 1.05% of variance, respectively), which is also the case for spot returns.

The VIX equation has relatively higher cross-market dependence, accounting for about 6.6% of the variance of forecast error. This indicates that equity market movement is indeed an important contributor to volatility expectations, further strengthening the relationship between the equity market and volatility perceptions of investors. Futures contributions to VIX are relatively small but not negligible, suggesting some information flow from derivatives to volatility expectations. Overall, the FEVD results show that each series is dominated by own-market shocks, but that there are meaningful spillovers between markets, especially futures-volatility and spot-volatility. The results provide strong evidence for the existence of both information flow and volatility spillover effects from and to the derivatives markets in the Indian equity markets.

Table 8. Conceived by Diebold-Yilmaz Spillover Index and Connectedness Measures.

Panel B: Exposure Risk Matrix (%)

From \ To	Spot	Futures	VIX
Spot	97.35	1.6	1.05
Futures	1.14	98.15	0.72
VIX	6.6	0.97	92.43

Panel B: Directional Spillovers

Market / Measure	TO Others (Transmission %)	FROM Others (Received %)	Net Spillover (%)	Total System Spillover Index (%)
Spot	2.65	7.74	-5.08	-
Futures	1.85	2.57	-0.71	-
VIX	7.57	1.77	5.8	-
System Index	-	-	-	4.02

Source: Authors Compilation.

The results of the Diebold-Yilmaz spillover index are summarized in Table 8, which shows the size and sign of volatility connectedness between spot returns, futures returns, and VIX returns. Most of the variance of forecast error is driven by internal shocks as the spillover matrix shows high own-market dominance, especially in futures (98.15%) and spot markets (97.35%). There are also considerable

spillovers from one market to another, though, in particular from the VIX to equity markets, indicating the significant role of volatility as a transmission mechanism of information.
The spillover analysis to others indicates that the VIX market is the biggest transmitter of shocks, followed by futures (1.85%) and spot (2.65%). This means that equity and derivatives markets are more susceptible to volatility shocks from the outside. The "FROM others" measure, on the other hand, reveals that spillovers to the spot market are the largest (7.74%), implying that the spot market is the most responsive market in the system.
The spillover effects net out further reinforce these. Overall there is a positive net spillover of 5.80% for the VIX making it the dominant information transmitter within the system. Spot and futures markets, on the other hand, are net receivers of shocks, with spot down (-5.08%) and futures down (-0.71%). Overall, the spillover index is 4.02%, which suggests a relatively low level of system-wide connectedness, but a statistically significant one, suggesting a high degree of partial market integration with limited, but statistically significant volatility transmission. Overall, the findings validate the hypothesis of asymmetric information flow, with volatility as the main determinant of spillovers between the Indian equity and derivatives markets.
Conclusion:
In this study, we analyzed the volatility transmission and spillover effects of the spot, futures, and VIX returns by using VAR, Granger causality, GARCH, FEVD, and Diebold–Yilmaz models. The outcomes indicate that there is strong interdependence among the three markets with clear evidence of "futures-led" price discovery, with futures returns Granger-causing spot returns, although the converse is not significant. Volatility models show that there is a substantial clustering effect and persistence in the data, suggesting long-lasting impacts of market shocks.
The results from the FEVD indicate that futures are more important than spot markets in explaining their fluctuations and that VIX is very important in explaining market uncertainty. The spillover analysis shows a large transmission effect from VIX to spot and futures markets, which are net receivers. The overall spillover index (4.02%) is a moderate but significant measure of market integration. The proposed model can be further expanded in future research with high-frequency data, regime-switching models, machine learning methods such as LSTM for better forecasting. The addition of global markets and macroeconomic variables would further improve the understanding of cross market and international volatility transmission. 4.02% index with high volatility clustering. Overall, these results highlight the importance of price trends in the derivatives market and that systemic risk is essentially linked to the concept of implied volatility, which makes it crucial for market participants and policymakers to closely watch VIX indicators to develop effective hedging strategies and prevent overall financial instability.

References

- Abid, M.F. et al. (2025) "Designing an information technology-enabled framework in the retail service ecosystem," Technological Forecasting and Social Change, 215, pp. 124078-124078. doi:10.1016/j.techfore.2025.124078.
- Bhattacharjee, A., Deb, S. and Das, J. (2025) "US-China geopolitical tensions and Indian stock market dynamics: evidence from NARDL and wavelet coherence," Bench Council Transactions on Benchmarks Standards and Evaluations, 5(4), pp. 100255-100255. doi:10.1016/j.tbench.2025.100255.
- Chen, J., Dong, X. and Lin, W. (2024) "The effects of e-commerce adoption on the financial performance of agri-food enterprises in China," Electronic commerce research [Preprint]. doi:10.1007/s10660-024-09810-z.
- CHENGYIN, G. and Salman, S.A. (2024) "A financial market study is an analysis of a trading platform where investors may trade financial securities and derivatives with minimal transaction costs.," Cuestiones de Fisioterapia, 53(3), pp. 2834-2846. doi:10.48047/9b1qhb49.

- Chi, X. et al. (2025) "Research on the volatility spillover effects of geopolitical conflict risks on international shipping and crude oil markets," Frontiers in Marine Science, 12. doi:10.3389/fmars.2025.1647599.
- Desai, M. et al. (2025) "Derivatives in Financial Market Development," International Journal for Multidisciplinary Research, 7(4). doi:10.36948/ijfmr.2025.v07i04.53789.
- Elsayed, A.H. et al. (2024) "Volatility spillover across spot and futures markets: Evidence from dual financial system," Research in International Business and Finance, 71, pp. 102473–102473. doi:10.1016/j.ribaf.2024.102473.
- Goldstein, I. and Yang, L. (2022) "Commodity Financialization and Information Transmission," TSpace, 77(5), pp. 2613-2667. doi:10.1111/jofi.13165.
- Han, S. (2026) "Volatility spillovers and portfolio diversification strategies after the 2023 Israel-Hamas conflict," Financial Innovation, 12(1). doi:10.1186/s40854-025-00850- 4.
- Ilmudeen, A. (2021) "Leveraging IT-enabled dynamic capabilities to shape business process agility and firm innovative capability: moderating role of turbulent environment," Review of Managerial Science, 16(8), pp. 2341-2379. doi:10.1007/s11846-021-00501-9.
- Kasraoui, C. et al. (2025) "Global Uncertainty and BRICS+ Equity Markets: Spillovers from VIX, Geopolitical Risk, and U.S. Macro-Financial Shocks," Risks, 13(11), pp. 217-217. doi:10.3390/risks13110217.
- Lubis, I., Hamidah, H. and Ulupui, I.G.K.A.U. (2026) "SLR on Geopolitical Risk, Commodities, Crypto, and Stocks," Jurnal Ilmu Keuangan dan Perbankan (JIKA), 15(1). doi:10.34010/jika.v15i1.16483.
- Reddy, Y.V. and Rao, K.S.H. (2025) "Indian stock market integration with global stock markets: An impulse and response analysis to global shocks," Asian Journal of Management and Commerce, 6(2), pp. 1388-1394. doi:10.22271/27084515.2025.v6.i2o.864.
- Salisu, A. and Abdul Hakeem, A. (2026) "The US-China tension, global supply disruptions and the agricultural commodity markets: a dynamic multivariate panel data analysis," Journal of Economic Studies, pp. 1-17. doi:10.1108/jes-10-2025-0832.
- Sharma, P. et al. (2025) "Does Price Discovery Process Hold during Post-COVID Period in Cryptocurrency? Evidence from Bitcoin," International Journal of Economics and Financial Issues, 15(5), pp. 317-322. doi:10.32479/ijefi.20427.
- Zhang, X. et al. (2025) "Dynamic Spillover Effects and its Influencing Factors in Commodity Futures Markets Under Major Shocks: Evidence from China's Edible Oils and Oil-seeds Futures," Paper Asia, 41, pp. 218-31. doi:10.59953/paperasia.v41i3b.442.