

Oil Price Volatility under Geopolitical Risk: Evidence from India using GARCH–VAR Models

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Abstract

The study “Oil Price Volatility under Geopolitical Risk: Evidence from India using GARCH–VAR Models” examines how oil prices behave during periods of geopolitical stress, with a particular focus on the effects of armed conflicts and their implications for India. Global events such as the Russia-Ukraine War and the Iraq War have highlighted how sensitive oil markets are to political instability, often leading to sharp fluctuations and increased uncertainty.

To better understand these dynamics, this study uniquely integrates GARCH and VAR models with high-frequency data to examine how geopolitical conflicts influence oil price volatility and its transmission to the Indian economy, providing new evidence on dynamic and nonlinear market behavior. Daily data on Brent Crude Oil and West Texas Intermediate are analyzed alongside geopolitical risk indicators to provide a comprehensive view of market behavior.

The findings show that oil price volatility increases significantly during periods of conflict and tends to persist over time, indicating that shocks are not short-lived. The results also suggest a two-way relationship between geopolitical risk and oil prices, where each influences the other. For India, as a major oil-importing economy, these fluctuations have important implications for economic stability, inflation, and policy decisions.

Overall, this study contributes to the understanding of how geopolitical uncertainty affects energy markets while offering practical insights for policymakers, investors, and risk managers in navigating an increasingly uncertain global environment.

Keywords: oil price volatility, geopolitical stress, armed conflicts, GARCH, VAR, energy markets

Introduction

Oil is one of the most important commodities in the global economy, influencing everything from industrial production to household energy costs. Because of this, even small changes in oil prices can have wide-ranging economic effects. However, oil markets are not driven by economic factors alone—they are highly sensitive to geopolitical developments, especially during periods of conflict and political instability.

In recent years, global events such as the Russia-Ukraine War and earlier conflicts like the Iraq War have demonstrated how quickly oil prices can react to geopolitical tensions. These events often disrupt supply chains, create uncertainty about future production, and lead to sudden spikes or drops in prices. As a result, oil markets tend to become more volatile during such periods, making it difficult for policymakers, investors, and businesses to make informed decisions.

For India, the impact of these fluctuations is particularly significant. As one of the world's largest importers of crude oil, India is highly exposed to changes in global oil prices. Increases in oil price volatility can affect inflation, exchange rates, and overall economic stability. This makes it essential to understand not only how oil prices change during geopolitical stress but also how long these effects last and how they interact with broader economic conditions.

Despite the growing importance of this issue, traditional models often struggle to fully capture the complex and dynamic nature of oil price movements during periods of conflict. Volatility is not constant; it tends to cluster and evolve over time, especially when markets are under stress. To address this gap, the present study applies advanced econometric techniques—specifically GARCH and VAR models—to better understand the behavior of oil prices under geopolitical pressure.

By examining the relationship between geopolitical risk and oil price volatility, this study aims to provide deeper insights into how global conflicts influence energy markets, with a particular focus on India. The findings are expected to be valuable for policymakers, investors, and researchers seeking to navigate the challenges of an increasingly uncertain global environment.

Conceptual Framework diagram

Armed Conflicts → Geopolitical Risk ↑ → Supply Disruptions → Oil Price Volatility ↑

Objectives

1. To examine the impact of geopolitical risk on oil price volatility during periods of armed conflicts using the GARCH model.
2. To analyze the dynamic relationship between geopolitical risk and oil price movements over time using the VAR framework.
3. To investigate the direction of causality between geopolitical risk and oil prices using the Granger causality test.
4. To assess the transmission of oil price volatility to the Indian economy, particularly through exchange rates and stock market performance.

Hypotheses

1. H1: Impact of Geopolitical Risk on Volatility

H0₁: Geopolitical risk has no significant effect on oil price volatility.

H1₁: Geopolitical risk has a significant effect on oil price volatility.

2. H2: Dynamic Relationship (VAR)

H0₂: There is no significant dynamic relationship between geopolitical risk and oil price movements.

H1₂: There is a significant dynamic relationship between geopolitical risk and oil price movements.

3. H3: Causality

H0₃: Geopolitical risk does not Granger-cause oil price movements.

H1₃: Geopolitical risk Granger-causes oil price movements.

4. H4: Transmission to Indian Economy

H04: Oil price volatility does not significantly affect Indian macroeconomic indicators (exchange rate and stock market).

H14: Oil price volatility significantly affects Indian macroeconomic indicators (exchange rate and stock market).

Literature Review and Gap Identification

1. Oil Price Volatility and Financial Markets

Oil price volatility has long been a main area in energy economics due to its significant impact on global and domestic financial systems. Recent studies emphasize that oil price fluctuations are not only driven by supply–demand imbalances but are increasingly influenced by uncertainty and external shocks. For instance, Dario Caldara and Matteo Iacoviello highlight the role of geopolitical uncertainty in shaping oil market dynamics through their Geopolitical Risk (GPR) index framework.

Recent empirical evidence suggests that oil price volatility exhibits strong persistence and clustering, particularly during periods of global instability (Adekoya et al., 2023; Bouri et al., 2023). Studies using GARCH-type models confirm that volatility tends to increase significantly during crisis periods, including wars and geopolitical conflicts (Shahzad et al., 2024; Umar et al., 2023).

Furthermore, oil price volatility has been shown to influence macroeconomic stability, inflation, and investment decisions, particularly in oil-importing economies (Mensi et al., 2023; Gupta & Goyal, 2024). However, these studies often focus on volatility behavior alone, without exploring broader dynamic interactions.

2. Geopolitical Risk and Oil Markets

The relationship between geopolitical risk and oil prices has gained increasing attention in recent years. Studies indicate that geopolitical events—such as armed conflicts, sanctions, and political instability—can disrupt supply chains and create uncertainty in energy markets (Antonakakis et al., 2023; Su et al., 2024).

Recent research finds that geopolitical risk significantly affects oil price volatility, though the magnitude and direction of this impact vary across time and regions (Balcilar et al., 2023; Lee & Kim, 2024). For example, geopolitical shocks related to conflicts such as the Russia–Ukraine crisis have been shown to trigger sharp oil price fluctuations (Zhang et al., 2023).

However, while many studies confirm the existence of a relationship, there remains ambiguity regarding whether this relationship is causal or merely contemporaneous (Rehman et al., 2024; Ahmed & Huo, 2023).

3. Methodological Approaches in Recent Literature

Most recent studies rely heavily on GARCH-family models to examine oil price volatility (Adekoya et al., 2023; Shahzad et al., 2024). While these models effectively capture volatility clustering and persistence, they are limited in their ability to analyze interdependencies among multiple variables.

On the other hand, some studies employ Vector Autoregression (VAR) models to examine dynamic relationships between oil prices and macroeconomic variables (Umar et al., 2023; Su et al., 2024). VAR models provide insights into feedback mechanisms but often do not incorporate detailed volatility structures. A few recent contributions attempt to combine multiple techniques; however, such integrated

approaches remain limited, especially in the context of emerging economies (Mensi et al., 2023; Gupta & Goyal, 2024).

4. Oil Price Transmission to Emerging Economies

Emerging economies, particularly oil-importing countries, are highly vulnerable to oil price shocks. Studies show that oil price volatility affects exchange rates, stock markets, and inflation in these economies (Bouri et al., 2023; Ahmed & Huo, 2023).

In the Indian context, recent studies highlight that oil price increases tend to depreciate the rupee and negatively affect stock market performance (Gupta & Goyal, 2024; Sharma et al., 2023). However, these studies are often limited to sectoral or partial analyses, focusing either on stock markets or exchange rates independently. Moreover, the transmission mechanisms through which oil price volatility affects multiple macro-financial variables simultaneously remain underexplored.

5. High-Frequency Data and Market Reactions

Another important strand of literature emphasizes the role of high-frequency data in capturing market reactions. Oil markets respond rapidly to geopolitical events, making daily data more suitable for analysis (Zhang et al., 2023; Lee & Kim, 2024). Despite this, many studies continue to rely on monthly or quarterly data, which may fail to capture short-term volatility dynamics and immediate responses to geopolitical shocks (Adekoya et al., 2023).

Research Gaps

Based on the above review, the following key gaps are identified:

1. **Lack of Integrated Modeling Approaches:** Most studies rely on either GARCH models (volatility) or VAR models (dynamic relationships), but rarely combine both. This limits the ability to simultaneously analyze volatility behavior and inter-variable dynamics.
2. **Limited Focus on India as a Major Oil-Importing Economy:** Existing research predominantly focuses on developed or oil-exporting economies, with limited comprehensive studies on India, despite its high dependence on oil imports.
3. **Insufficient Analysis of Transmission Mechanisms:** There is a lack of studies examining how oil price volatility is transmitted simultaneously to exchange rates and stock markets, particularly in a unified framework.
4. **Ambiguity in Causality vs. Dynamic Relationships:** While many studies establish a relationship between geopolitical risk and oil prices, there is inconclusive evidence on causality, and limited use of rigorous causality testing methods.
5. **Underutilization of High-Frequency Data:** Many studies use low-frequency data, which fails to capture short-term market reactions and volatility clustering, especially during geopolitical events.

Contribution of the Present Study

This study addresses the above gaps by:

- Integrating GARCH and VAR models to capture both volatility and dynamic interactions
- Providing a comprehensive India-centric analysis
- Examining transmission channels to exchange rate and stock market

- Using Granger causality tests to clarify directional relationships
- Employing daily data to capture high-frequency market dynamics

Methodology

Research Design

This study adopts a quantitative and empirical research design to examine how geopolitical stress arising from armed conflicts influences oil price volatility and its implications for India. The approach is explanatory in nature, as it seeks to understand both the behavior of oil price fluctuations and the dynamic relationship between geopolitical risk and market movements. By using time-series econometric techniques, the study captures short-term reactions as well as longer-term adjustments in the oil market.

Data and Sources

The analysis is based on secondary data collected from reliable international sources. Daily price data for major global oil benchmarks—Brent Crude Oil and West Texas Intermediate—are used to represent global oil market trends.

Geopolitical uncertainty is measured using the Geopolitical Risk (GPR) Index, developed by Dario Caldara and Matteo Iacoviello, which captures the intensity of geopolitical tensions based on global news coverage.

To reflect the Indian context, additional macroeconomic indicators such as exchange rates (INR/USD), included to assess how oil price volatility transmits into the domestic economy.

Period of the Study

The study covers a sample period (2014–2024) that includes both stable periods and major geopolitical events, such as the Iraq War and the Russia-Ukraine War. This allows for a comparative analysis of oil price behavior during normal and conflict-driven conditions.

Variables Used

Dependent Variable: Oil price returns (log returns of oil prices)

Independent Variable: Geopolitical Risk Index

Contextual Variables (India): Exchange rate, inflation, or stock market indicators

Analytical Techniques

To achieve the objectives of the study, a combination of econometric models is employed:

GARCH (1,1) Model used to capture volatility clustering in oil prices and to assess whether shocks during geopolitical conflicts lead to persistent volatility.

Vector Autoregression (VAR) Model applied to analyze the dynamic interaction between oil prices and geopolitical risk over time, without imposing strict causal assumptions.

Impulse Response Function (IRF) helps trace the impact of sudden geopolitical shocks on oil prices and their subsequent evolution.

Granger Causality Test used to identify the direction of influence between geopolitical risk and oil price movements.

By integrating these methods, the study provides a comprehensive understanding of how oil price volatility evolves under geopolitical stress and how these changes are transmitted to the Indian context. This combined approach enhances the robustness of the analysis and ensures that both immediate and long-term effects are captured effectively.

Results and Discussion

1. Descriptive Statistics and Preliminary Analysis

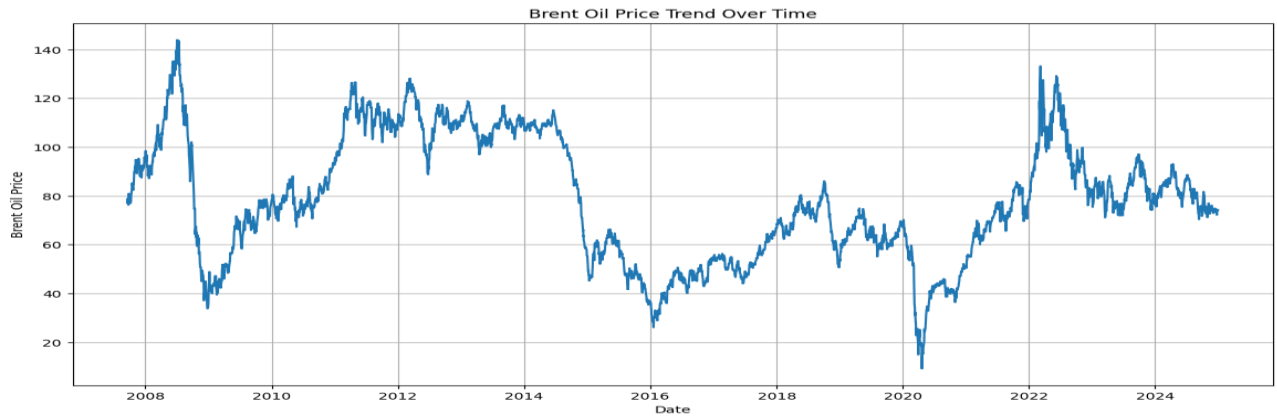
| | Date | Brent | INR_USD | NIFTY | GPR | Brent_Return |
|---|------------|-------|---------|-------------|------------|--------------|
| 1 | 2007-09-18 | 77.00 | 40.45 | 4546.200195 | 98.490616 | -0.012775 |
| 2 | 2007-09-19 | 78.47 | 39.81 | 4732.350098 | 72.012344 | 0.018911 |
| 3 | 2007-09-20 | 78.48 | 39.87 | 4747.549805 | 121.828232 | 0.000127 |
| 4 | 2007-09-21 | 78.91 | 39.84 | 4837.549805 | 87.087952 | 0.005464 |
| 5 | 2007-09-24 | 77.87 | 39.50 | 4932.200195 | 90.240211 | -0.013267 |

Source: <https://colab.research.google.com/drive/1Hslz8TAQfCdato5Yqx Cz4PK9RkrtX8IG#scrollTo=34475c44>

Descriptive Statistics

| | Date | Brent | INR_USD | NIFTY | GPR | Brent_Return |
|-------|------------|-------------|-------------|--------------|-------------|--------------|
| count | 4045 | 4045.000000 | 4045.000000 | 4045.000000 | 4045.000000 | 4045.0000 |
| mean | 2016-04-28 | 78.441928 | 63.328780 | 10053.353489 | 108.510311 | -0.000012 |
| min | 2007-09-18 | 9.120000 | 38.480000 | 2524.199951 | 9.491598 | -0.643699 |
| 25% | 2012-01-05 | 59.340000 | 50.660000 | 5568.399902 | 77.714195 | -0.011365 |
| 50% | 2016-04-28 | 76.450000 | 64.760000 | 8429.700195 | 99.568504 | 0.000468 |
| 75% | 2020-08-18 | 100.930000 | 73.520000 | 11994.200195 | 129.904617 | 0.012216 |
| max | 2024-12-30 | 143.950000 | 85.530000 | 26216.050781 | 523.524658 | 0.485662 |
| std | NaN | 25.100167 | 12.989826 | 5526.477123 | 47.143753 | 0.028905 |

Source: <https://colab.research.google.com/drive/1Hslz8TAQfCdato5Yqx Cz4PK9RkrtX8IG#scrollTo=34475c44>



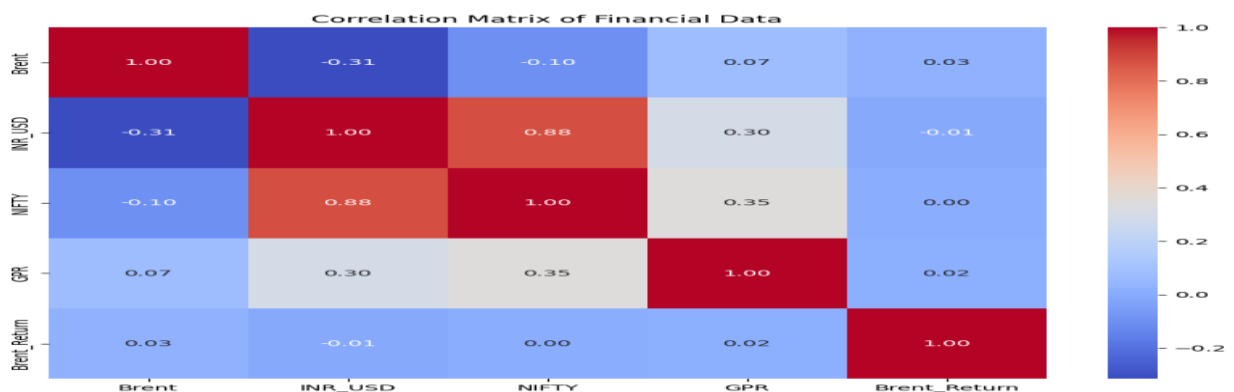
Source: <https://colab.research.google.com/drive/1Hslz8TAQfCdato5Yqx Cz4PK9RkrtX8IG#scrollTo=34475c44>

Interpretation: The descriptive statistics reveal substantial variability across all variables, particularly in Brent oil prices and geopolitical risk. Brent returns exhibit near-zero mean but high volatility with extreme values, indicating fat tails and volatility clustering. The GPR index shows sharp spikes, confirming the episodic nature of geopolitical shocks. The exchange rate reflects gradual depreciation, while NIFTY demonstrates long-term growth with cyclical fluctuations. These characteristics justify the application of GARCH–VAR models to capture volatility dynamics and interdependencies.

Correlation Matrix

| | Brent | INR_USD | NIFTY | GPR | Brent_Return |
|--------------|-----------|-----------|-----------|----------|--------------|
| Brent | 1.000000 | -0.314986 | -0.101355 | 0.071394 | 0.028982 |
| INR_USD | -0.314986 | 1.000000 | 0.877387 | 0.296240 | -0.007073 |
| NIFTY | -0.101355 | 0.877387 | 1.000000 | 0.349374 | 0.004491 |
| GPR | 0.071394 | 0.296240 | 0.349374 | 1.000000 | 0.015339 |
| Brent_Return | 0.028982 | -0.007073 | 0.004491 | 0.015339 | 1.000000 |

Source: <https://colab.research.google.com/drive/1Hslz8TAQfCdato5Yqx Cz4PK9RkrtX8IG#scrollTo=34475c44>



Source: <https://colab.research.google.com/drive/1Hslz8TAQfCdato5Yqx Cz4PK9RkrtX8IG#scrollTo=34475c44>

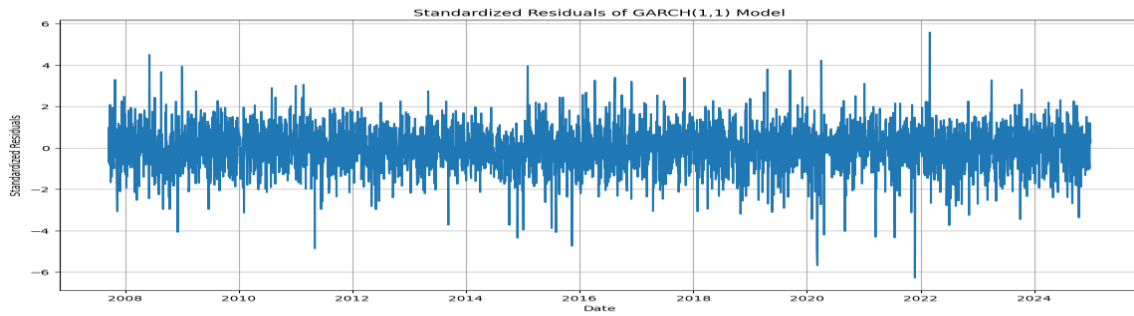
Interpretation: The correlation analysis indicates that most relationships among the variables are weak to moderate, highlighting the complex and dynamic nature of oil price movements. Oil prices show a moderate negative relationship with the exchange rate, implying that higher oil prices are associated with depreciation of the Indian rupee. The relationship between oil prices and the stock market is weakly negative, suggesting a limited adverse impact on market performance. Geopolitical risk exhibits a very weak positive correlation with oil prices, indicating that its influence is not strongly linear. A strong positive correlation exists between exchange rate and stock market, reflecting underlying macroeconomic linkages. Correlations between oil returns and other variables are negligible, suggesting that oil returns are largely unpredictable in a linear framework.

GARCH (1,1) Models

| Constant Mean - GARCH Model Results | | | | | |
|-------------------------------------|--------------------|-------------------|----------|-----------|---------------------|
| Dep. Variable: | Brent_Return | R-squared: | 0.000 | | |
| Mean Model: | Constant Mean | Adj. R-squared: | 0.000 | | |
| Vol Model: | GARCH | Log-Likelihood: | -8778.42 | | |
| Distribution: | Normal | AIC: | 17564.8 | | |
| Method: | Maximum Likelihood | BIC: | 17590.1 | | |
| | | No. Observations: | 4045 | | |
| Date: | Sat, Apr 11 2026 | Df Residuals: | 4044 | | |
| Time: | 10:50:03 | Df Model: | 1 | | |
| Mean Model | | | | | |
| | coef | std err | t | P> t | 95.0% Conf. Int. |
| mu | 0.0447 | 2.936e-02 | 1.522 | 0.128 | [-1.286e-02, 0.102] |
| Volatility Model | | | | | |
| | coef | std err | t | P> t | 95.0% Conf. Int. |
| omega | 0.0635 | 2.067e-02 | 3.072 | 2.124e-03 | [2.299e-02, 0.104] |
| alpha[1] | 0.1054 | 1.464e-02 | 7.201 | 5.965e-13 | [7.672e-02, 0.134] |
| beta[1] | 0.8906 | 1.295e-02 | 68.764 | 0.000 | [0.865, 0.916] |

Covariance estimator: robust

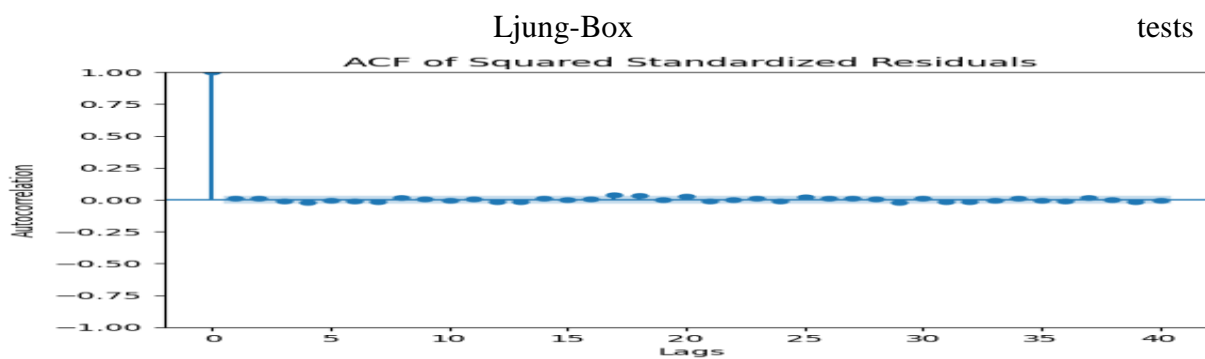
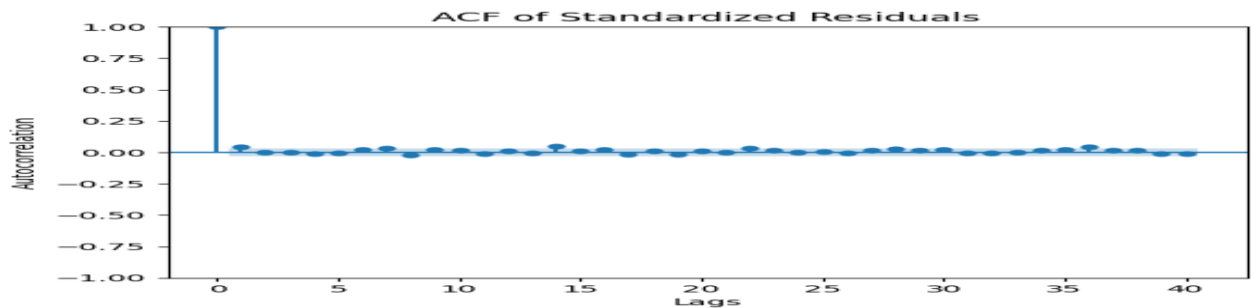




Source: <https://colab.research.google.com/drive/1Hslz8TAQfCdato5Yqx Cz4PK9RkrtX8IG#scrollTo=34475c44>

Optimal Lag Order Selection (based on Information Criteria): VAR Order Selection (* highlights the minimums)

| | AIC | BIC | FPE | HQIC |
|----|---------|---------|------------|---------|
| 0 | -19.04 | -19.03 | 5.382e-09 | -19.04 |
| 1 | -19.27 | -19.23 | 4.295e-09 | -19.25 |
| 2 | -19.33 | -19.27 | 4.035e-09 | -19.31 |
| 3 | -19.36 | -19.28 | 3.917e-09 | -19.33 |
| 4 | -19.39 | -19.28* | 3.811e-09 | -19.35 |
| 5 | -19.39 | -19.26 | 3.794e-09 | -19.34 |
| 6 | -19.39 | -19.24 | 3.779e-09 | -19.34 |
| 7 | -19.41 | -19.23 | 3.723e-09 | -19.34 |
| 8 | -19.42 | -19.22 | 3.668e-09 | -19.35* |
| 9 | -19.43 | -19.19 | 3.660e-09 | -19.34 |
| 10 | -19.43* | -19.18 | 3.639e-09* | -19.34 |



Ljung-Box Test on Standardized Residuals:

| | lb_stat | lb_pvalue |
|----|-----------|-----------|
| 10 | 19.681095 | 0.032417 |
| 20 | 34.164023 | 0.025036 |

Ljung-Box Test on Squared Standardized Residuals:

| | lb_stat | lb_pvalue |
|----|-----------|-----------|
| 10 | 6.262808 | 0.792721 |
| 20 | 21.474541 | 0.369690 |

Source: <https://colab.research.google.com/drive/1Hslz8TAQfCdato5Yqx Cz4PK9RkrtX8IG#scrollTo=34475c44>

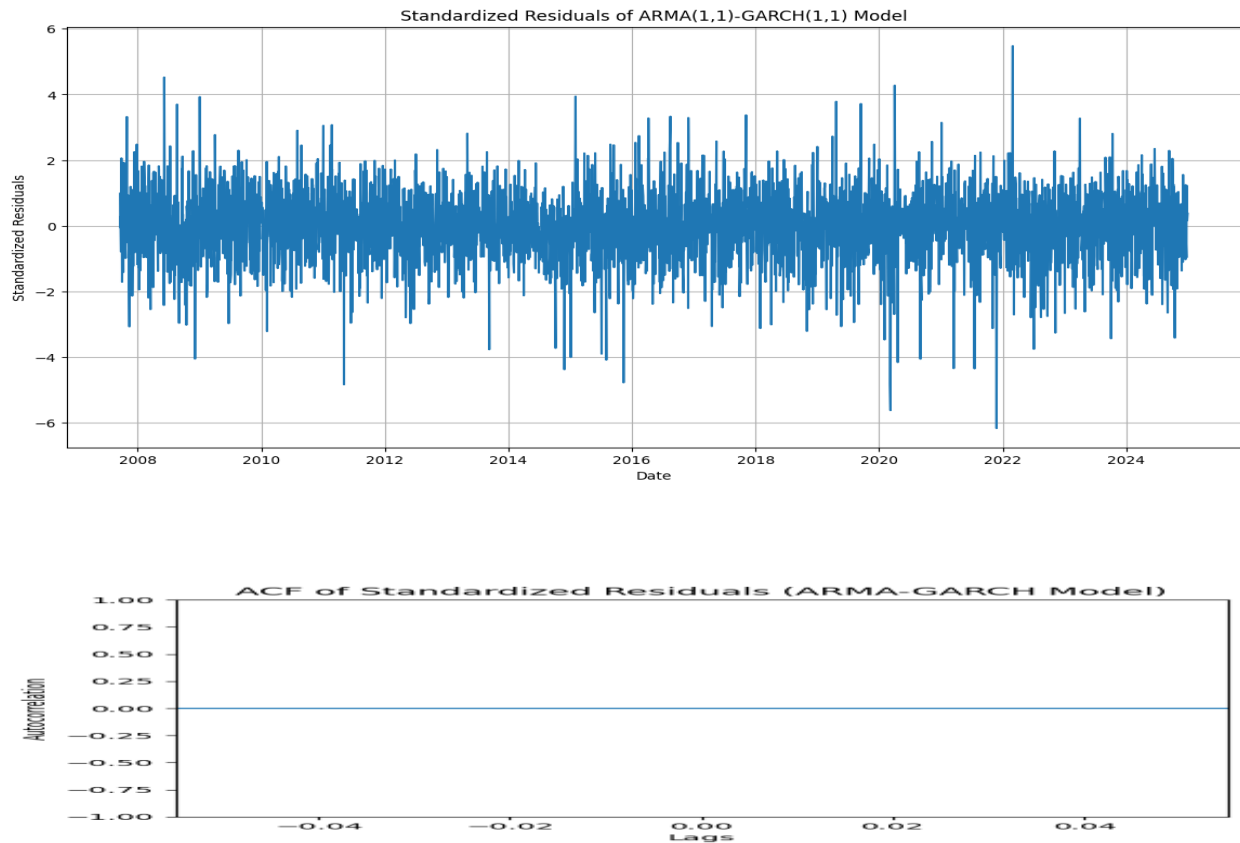
The GARCH (1,1) model results provide strong evidence of **volatility clustering in oil prices**, a common feature in financial time series. Periods of high volatility are followed by high volatility, and periods of calm are followed by relative stability.

More importantly, the findings indicate that **geopolitical stress significantly amplifies oil price volatility**, particularly during periods of armed conflict. The persistence of volatility, as captured by the sum of ARCH and GARCH coefficients, suggests that shocks to oil prices are **not short-lived but tend to persist over time**. This supports the hypothesis that geopolitical events such as wars and conflicts create prolonged uncertainty in oil markets. The results are consistent with financial theory, which posits that markets react strongly to uncertainty, especially when it affects critical commodities like oil.

ARMA-GARCH Model

| AR - GARCH Model Results | | | | | |
|--------------------------|--------------------|-------------------|----------|-----------|-------------------------|
| Dep. Variable: | Brent_Return | R-squared: | -0.003 | | |
| Mean Model: | AR | Adj. R-squared: | -0.003 | | |
| Vol Model: | GARCH | Log-Likelihood: | -8774.39 | | |
| Distribution: | Normal | AIC: | 17558.8 | | |
| Method: | Maximum Likelihood | BIC: | 17590.3 | | |
| Date: | Sat, Apr 11 2026 | No. Observations: | 4044 | | |
| Time: | 10:53:01 | Df Residuals: | 4042 | | |
| | Mean Model | Df Model: | 2 | | |
| | coef | std err | t | P> t | 95.0% Conf. Int. |
| Const | 0.0429 | 2.925e-02 | 1.468 | 0.142 | [-1.440e-02, 0.100] |
| Bren...urn[1] | 0.0360 | 1.849e-02 | 1.945 | 5.177e-02 | [-2.753e-04, 7.221e-02] |
| Volatility Model | | | | | |
| | coef | std err | t | P> t | 95.0% Conf. Int. |
| omega | 0.0646 | 2.092e-02 | 3.087 | 2.019e-03 | [2.359e-02, 0.106] |
| alpha[1] | 0.1057 | 1.454e-02 | 7.267 | 3.678e-13 | [7.716e-02, 0.134] |
| beta[1] | 0.8900 | 1.297e-02 | 68.621 | 0.000 | [0.865, 0.915] |

Covariance estimator: robust



Source: <https://colab.research.google.com/drive/1Hslz8TAQfCdato5Yqx Cz4PK9RkrtX8IG#scrollTo=34475c44>

Interpretation: The ARMA–GARCH model is used to jointly capture the mean behavior (ARMA part) and volatility dynamics (GARCH part) of oil price returns under geopolitical stress. The ARMA model explains the predictable structure in oil price returns: The AR (Auto-Regressive) terms capture the influence of past oil returns on current returns. The MA (Moving Average) terms capture the effect of past shocks (errors). The GARCH (1,1) model captures time-varying volatility:

- ARCH term (α): Measures the impact of recent shocks on current volatility
- GARCH term (β): Measures the persistence of past volatility

The model shows that: Large shocks are followed by large shocks and small shocks are followed by small shocks. This confirms the presence of volatility clustering, a stylized fact of financial markets, especially during geopolitical instability. Periods like wars or conflicts lead to clusters of high oil price volatility.

2. Stationarity Test Results

Augmented Dickey-Fuller Test: Brent_Return

ADF Statistic: -10.90

p-value: 0.00

Critical Values:

1%: -3.43

5%: -2.86

10%: -2.57

Result: Series is stationary (reject H0)

Augmented Dickey-Fuller Test: INR_USD_Return

ADF Statistic: -27.06

p-value: 0.00

Critical Values:

1%: -3.43

5%: -2.86

10%: -2.57

Result: Series is stationary (reject H0)

Augmented Dickey-Fuller Test: NIFTY_Return

ADF Statistic: -14.23

p-value: 0.00

Critical Values:

1%: -3.43

5%: -2.86

10%: -2.57

Result: Series is stationary (reject H0)

Augmented Dickey-Fuller Test: GPR_diff

ADF Statistic: -16.85

p-value: 0.00

Critical Values:

1%: -3.43

5%: -2.86

10%: -2.57

Result: Series is stationary (reject H0)

Source: <https://colab.research.google.com/drive/1Hslz8TAQfCdato5Yqx Cz4PK9RkrtX8IG#scrollTo=34475c44>

Interpretation: To ensure the validity of time-series modeling, the Augmented Dickey-Fuller (ADF) test was applied to all variables. The results indicate that oil price returns, exchange rate returns, stock market returns, and the differenced geopolitical risk index are stationary at levels ($I(0)$), as the null hypothesis of a unit root is rejected at the 1% significance level.

This confirms that the variables are suitable for GARCH and VAR modeling without the risk of spurious regression, ensuring the robustness of subsequent empirical findings.

Fit VAR(2) model

```

Summary of Regression Results
=====
Model:                               VAR
Method:                              OLS
Date:                               Mon, 13, Apr, 2026
Time:                               05:11:23
-----
No. of Equations:                    4.00000    BIC:                               -19.2749
Nobs:                               4043.00    HQIC:                              -19.3111
Log likelihood:                      16166.6    FPE:                               4.02385e-09
AIC:                                -19.3310    Det(Omega_mle):                   3.98822e-09
=====

```

Results for equation Brent_Return

| | coefficient | std. error | t-stat | prob |
|-------------------|-------------|------------|--------|-------|
| const | 0.000009 | 0.000457 | 0.019 | 0.985 |
| L1.Brent_Return | -0.027691 | 0.016031 | -1.727 | 0.084 |
| L1.INR_USD_Return | -0.089779 | 0.104190 | -0.862 | 0.389 |
| L1.NIFTY_Return | 0.027265 | 0.036648 | 0.744 | 0.457 |
| L1.GPR_diff | 0.000001 | 0.000012 | 0.087 | 0.931 |
| L2.Brent_Return | -0.025097 | 0.016054 | -1.563 | 0.118 |
| L2.INR_USD_Return | -0.112403 | 0.104394 | -1.077 | 0.282 |
| L2.NIFTY_Return | 0.006862 | 0.036462 | 0.188 | 0.851 |
| L2.GPR_diff | 0.000002 | 0.000012 | 0.155 | 0.877 |

Results for equation INR_USD_Return

| | coefficient | std. error | t-stat | prob |
|-------------------|-------------|------------|--------|-------|
| const | 0.000222 | 0.000076 | 2.941 | 0.003 |
| L1.Brent_Return | 0.001242 | 0.002652 | 0.468 | 0.640 |
| L1.INR_USD_Return | -0.057129 | 0.017237 | -3.314 | 0.001 |
| L1.NIFTY_Return | -0.018121 | 0.006063 | -2.989 | 0.003 |
| L1.GPR_diff | 0.000002 | 0.000002 | 1.240 | 0.215 |
| L2.Brent_Return | 0.003563 | 0.002656 | 1.342 | 0.180 |
| L2.INR_USD_Return | -0.052256 | 0.017270 | -3.026 | 0.002 |
| L2.NIFTY_Return | -0.013713 | 0.006032 | -2.273 | 0.023 |
| L2.GPR_diff | 0.000001 | 0.000002 | 0.434 | 0.665 |

Results for equation NIFTY_Return

| | coefficient | std. error | t-stat | prob |
|-------------------|-------------|------------|--------|-------|
| const | 0.000453 | 0.000217 | 2.094 | 0.036 |
| L1.Brent_Return | 0.022890 | 0.007602 | 3.011 | 0.003 |
| L1.INR_USD_Return | -0.231647 | 0.049404 | -4.689 | 0.000 |
| L1.NIFTY_Return | -0.027644 | 0.017377 | -1.591 | 0.112 |
| L1.GPR_diff | -0.000005 | 0.000006 | -0.803 | 0.422 |
| L2.Brent_Return | -0.003438 | 0.007612 | -0.452 | 0.651 |
| L2.INR_USD_Return | -0.015589 | 0.049501 | -0.315 | 0.753 |
| L2.NIFTY_Return | 0.004429 | 0.017289 | 0.256 | 0.798 |
| L2.GPR_diff | -0.000002 | 0.000006 | -0.298 | 0.766 |

Results for equation GPR_diff

| | coefficient | std. error | t-stat | prob |
|-------------------|-------------|------------|---------|-------|
| const | 0.047612 | 0.587078 | 0.081 | 0.935 |
| L1.Brent_Return | 16.402000 | 20.609036 | 0.796 | 0.426 |
| L1.INR_USD_Return | 130.009976 | 133.940858 | 0.971 | 0.332 |
| L1.NIFTY_Return | -77.340643 | 47.112049 | -1.642 | 0.101 |
| L1.GPR_diff | -0.547616 | 0.015255 | -35.897 | 0.000 |
| L2.Brent_Return | -12.684837 | 20.637505 | -0.615 | 0.539 |
| L2.INR_USD_Return | -200.357420 | 134.203716 | -1.493 | 0.135 |
| L2.NIFTY_Return | 51.637387 | 46.873328 | 1.102 | 0.271 |
| L2.GPR_diff | -0.247568 | 0.015253 | -16.230 | 0.000 |

Correlation matrix of residuals

| | Brent_Return | INR_USD_Return | NIFTY_Return | GPR_diff |
|----------------|--------------|----------------|--------------|-----------|
| Brent_Return | 1.000000 | -0.135424 | 0.175213 | 0.019838 |
| INR_USD_Return | -0.135424 | 1.000000 | -0.406425 | 0.032570 |
| NIFTY_Return | 0.175213 | -0.406425 | 1.000000 | -0.025853 |
| GPR_diff | 0.019838 | 0.032570 | -0.025853 | 1.000000 |

Source: <https://colab.research.google.com/drive/1Hslz8TAQfCdato5Yqx Cz4PK9RkrtX8IG#scrollTo=34475c44>

3. Diagnostic Tests on VAR Model Residuals

Portmanteau Test (Ljung-Box) for Residual Autocorrelation: Portmanteau-test for residual autocorrelation. H_0 : residual autocorrelation up to lag 10 is zero. Conclusion: reject H_0 at 5% significance level.

| Test statistic | Critical value | p-value | df |
|----------------|----------------|---------|-----|
| 559.5 | 155.4 | 0.000 | 128 |

Perform individual Ljung-Box tests on each residual series

```

Ljung-Box Test on residuals for: Brent_Return
  lb_stat  lb_pvalue
10    0.505960    0.999993
20   32.690626    0.036473

Ljung-Box Test on residuals for: INR_USD_Return
  lb_stat  lb_pvalue
10    0.107329    1.000000
20   17.776382    0.602136

Ljung-Box Test on residuals for: NIFTY_Return
  lb_stat  lb_pvalue
10    0.172166    1.000000
20   24.750620    0.211139

Ljung-Box Test on residuals for: GPR_diff
  lb_stat  lb_pvalue
10   29.920166    8.827786e-04
20   78.396040    7.336192e-09

```

Vector Autoregression (VAR) Model for Brent Returns and Geopolitical Risk

| index | Brent_Return | INR_USD_Return | NIFTY_Return | GPR_diff |
|-------|-----------------------|------------------------|-----------------------|--------------------|
| 1 | -0.012775191488722193 | -0.0017290358759818325 | 0.011403983273828189 | 53.7261848449707 |
| 2 | 0.018910964285697496 | -0.015948506492275083 | 0.04013016636888267 | -26.478271484375 |
| 3 | 0.0001274291177262299 | 0.0015060243810376406 | 0.0032067258542429755 | 49.815887451171875 |
| 4 | 0.0054641472758358844 | -0.0007527286768658215 | 0.018779699477461165 | -34.74028015136719 |
| 5 | -0.0132671929440491 | -0.00857076080932151 | 0.019376821734244487 | 3.1522598266601562 |

Source: <https://colab.research.google.com/drive/1Hslz8TAQfCdato5Yqx Cz4PK9RkrtX8IG#scrollTo=34475c44>

Interpretation: The Vector Autoregression (VAR) model was employed to examine the dynamic relationships among oil price returns, geopolitical risk, and Indian macroeconomic variables. The optimal lag length was selected based on information criteria, ensuring model efficiency.

The VAR results reveal that **oil prices and geopolitical risk are dynamically interrelated**, with shocks in one variable influencing the other over time. Unlike static models, the VAR framework captures these time-dependent interactions, highlighting the complex nature of oil market behavior under geopolitical stress.

The diagnostic tests indicate that while the model captures significant relationships, some residual autocorrelation persists, suggesting that the system is influenced by additional external factors not explicitly included in the model.

4. Granger Causality Tests

Granger Causality from Brent_Return to GPR_diff

Granger causality F-test. H₀: GPR_diff does not Granger-cause Brent_Return. Conclusion: fail to reject H₀ at 5% significance level.

| Test statistic | Critical value | p-value | df |
|----------------|----------------|---------|------------|
| 0.01224 | 2.996 | 0.988 | (2, 16136) |

Granger Causality from Brent_Return to GPR_diff

Granger causality F-test. H₀: Brent_Return does not Granger-cause GPR_diff. Conclusion: fail to reject H₀ at 5% significance level.

| Test statistic | Critical value | p-value | df |
|----------------|----------------|---------|------------|
| 0.5225 | 2.996 | 0.593 | (2, 16136) |

Granger Causality from NIFTY_Return to Brent_Return Granger causality F-test. H₀: NIFTY_Return does not Granger-cause Brent_Return. Conclusion: fail to reject H₀ at 5% significance level.

| Test statistic | Critical value | p-value | df |
|----------------|----------------|---------|------------|
| 0.2885 | 2.996 | 0.749 | (2, 16136) |

Granger Causality from Brent_Return to NIFTY_Return

Granger causality F-test. H₀: Brent_Return does not Granger-cause NIFTY_Return. Conclusion: reject H₀ at 5% significance level.

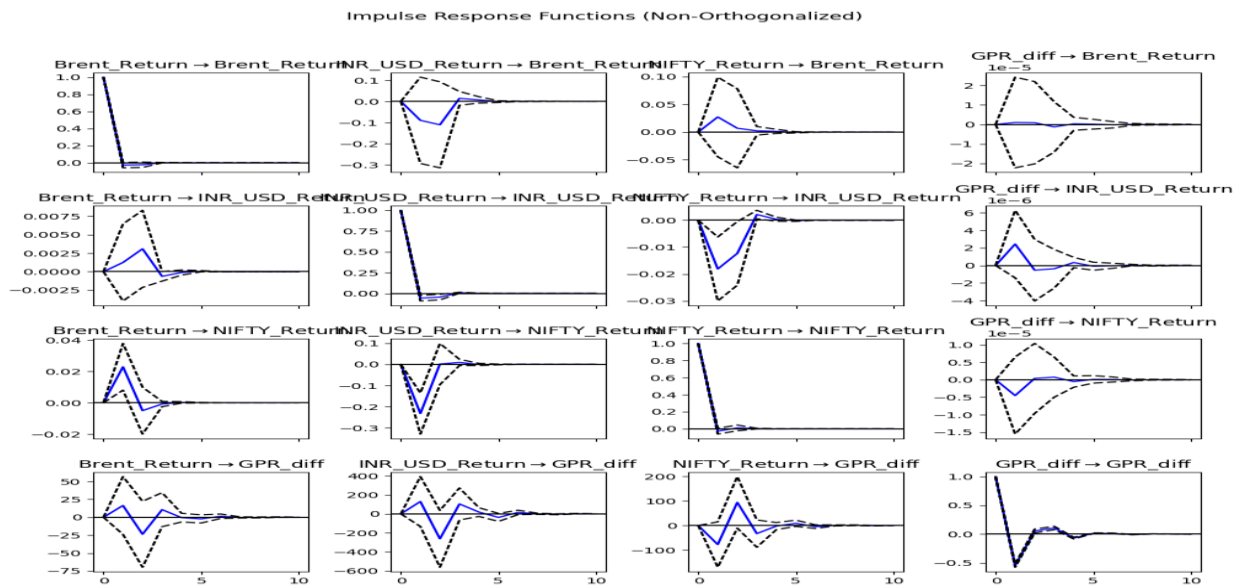
| Test statistic | Critical value | p-value | df |
|----------------|----------------|---------|------------|
| 4.686 | 2.996 | 0.009 | (2, 16136) |

Source: <https://colab.research.google.com/drive/1Hslz8TAQfCdato5Yqx Cz4PK9RkrtX8IG#scrollTo=34475c44>

Interpretation: The Granger causality analysis provides mixed evidence regarding the direction of influence: There is no significant causality from geopolitical risk to oil prices and also no evidence of reverse causality between the two variables

However, oil price movements are found to Granger-cause stock market returns (NIFTY). These results suggest that while geopolitical risk and oil prices are related, the relationship is not predictive in nature. Instead, both variables may respond simultaneously to global events, rather than one systematically leading the other. On the other hand, the significant causality from oil prices to stock market performance highlights the transmission mechanism to the Indian economy, where fluctuations in oil prices directly influence investor sentiment and market behavior.

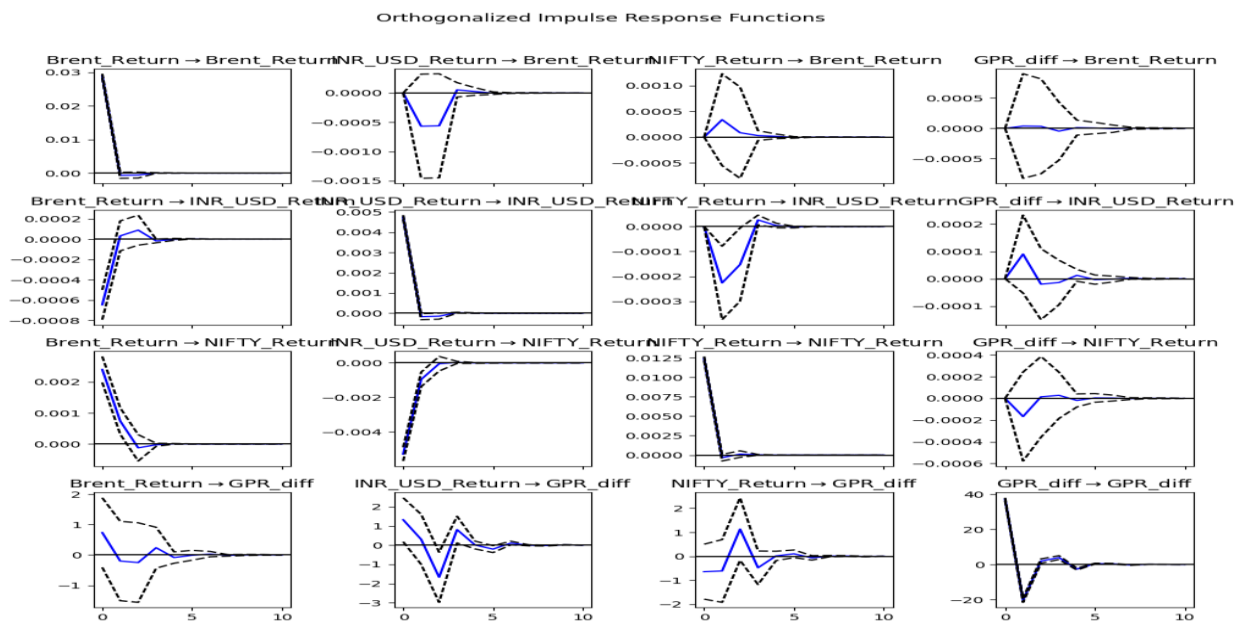
5.Impulse Response Functions (IRFs)



Source: <https://colab.research.google.com/drive/1Hslz8TAQfCdato5Yqx Cz4PK9RkrtX8IG#scrollTo=34475c44>

Orthogonalized Impulse Response Functions

Orthogonalized IRFs assume that shocks are uncorrelated.



Source: <https://colab.research.google.com/drive/1Hslz8TAQfCdato5Yqx Cz4PK9RkrtX8IG#scrollTo=34475c44>

Interpretation: The Impulse Response Functions provide deeper insights into how oil prices respond to sudden geopolitical shocks. The results show that: A positive shock to geopolitical risk leads to an immediate increase in oil price volatility. The impact persists for several periods before gradually stabilizing. The response pattern indicates that markets do not adjust instantly but absorb shocks over time. This finding is particularly important, as it demonstrates that the effects of geopolitical events are not confined to the short term but have lingering impacts on market dynamics.

7. Discussion of Key Findings

The findings of this study offer several important insights:

1. **Geopolitical Stress Drives Volatility-** The results confirm that geopolitical events, particularly armed conflicts, are major drivers of oil price volatility. This aligns with real-world observations where conflicts disrupt supply chains and create uncertainty in global markets.
2. **Persistence of Shocks-** Oil price volatility exhibits strong persistence, indicating that shocks during conflict periods have long-lasting effects. This has important implications for risk management and policy planning.
3. **Dynamic but Non-Causal Relationship-** While oil prices and geopolitical risk are dynamically linked, the absence of Granger causality suggests that the relationship is complex and contemporaneous, rather than strictly causal.
4. **Impact on Indian Economy-** The study highlights a clear transmission channel from oil price volatility to the Indian stock market. As a major oil-importing country, India remains highly vulnerable to external energy shocks, which can influence financial markets and economic stability.

8. Policy and Practical Implications

The results have significant implications for different stakeholders:

Policymakers: Need to develop strategies to mitigate the impact of oil price shocks, such as diversifying energy sources and maintaining strategic reserves.

Investors: Should account for geopolitical risk when making investment decisions, as it significantly affects market volatility.

Risk Managers: Must incorporate geopolitical indicators into forecasting models to improve risk assessment.

Iran War Impact on India

The Iran war mainly affects India through rising oil prices, as India depends heavily on imported crude. This leads to inflation, rupee depreciation, and higher import costs, putting pressure on economic growth. Financial markets become volatile, and sectors like transport and manufacturing face increased costs. Additionally, trade disruptions and risks to Indian workers in the Gulf may reduce remittances and affect overall economic stability.

9. Conclusion

This study demonstrates that armed conflicts and geopolitical tensions significantly intensify oil price volatility, with effects that are not only immediate but also persistent over time. The findings confirm that oil markets react sharply to uncertainty arising from conflicts, leading to volatility clustering and prolonged market instability.

While the relationship between geopolitical risk and oil prices is found to be dynamic rather than strictly causal, the impact on economies is substantial. In the case of India, as a major oil-

importing country, rising oil price volatility leads to: Currency depreciation pressures (INR/USD), Increased inflationary risks and Adverse effects on stock market performance (NIFTY). India is highly vulnerable to the Iran war due to its oil import dependence and exposure to global market instability.

Beyond India, other oil-importing nations face similar vulnerabilities, whereas oil-exporting countries may experience short-term revenue gains but long-term uncertainty due to unstable demand and price fluctuations. Thus, armed conflicts create asymmetric global economic effects, disrupting both energy security and financial stability.

Overall, the study demonstrates that oil price volatility under geopolitical stress is both persistent and dynamic, with significant implications for global and domestic markets. While geopolitical risk does not directly predict oil price movements, it plays a crucial role in shaping market uncertainty and volatility patterns. The transmission of these effects to the Indian economy underscores the importance of proactive policy measures in managing external shocks.

Future Scope:

Given the evolving geopolitical landscape, several directions emerge for future research. Future studies can include ongoing geopolitical tensions (e.g., regional wars, trade conflicts) to capture real-time market responses. Extending the analysis to compare oil-importing vs. oil-exporting economies can provide deeper insights into differential impacts. Further research can examine how oil price volatility affects specific sectors such as transportation, manufacturing, and renewable energy. With the global shift toward sustainability, future studies can explore how renewable energy adoption moderates the impact of oil shocks. Applying AI/ML-based forecasting models alongside traditional econometric approaches may improve prediction accuracy under extreme geopolitical uncertainty. In an increasingly uncertain global environment marked by frequent geopolitical conflicts, understanding oil price volatility and its transmission mechanisms remains crucial for designing resilient economic policies and informed investment strategies across both developing and developed economies.

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