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# Geopolitical Sentiment as a Leading Indicator: A Hybrid Analytics Approach to Forecasting Oil Volatility and Emerging Market Vulnerability (2015–2025)

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**Abstract**

This study examines the impact of geopolitical risk on international oil prices, defense sector performance, and emerging market currencies using an integrated hybrid analytical framework. The framework combines GARCH-based volatility modeling, event study analysis, sentiment scoring, and machine learning (XGBoost) to capture market responses to geopolitical shocks. The analysis covers 30+ major conflict events from 2015–2025, including the Russia–Ukraine crisis, Iran–Israel tensions, and repeated confrontations in the Red Sea. Event-specific sentiment scores, derived via TextBlob, quantify the effect of news sentiment on financial markets. Empirical results reveal significant volatility clustering in oil prices around conflict dates, with an average post-event increase of 6.8%, and consistent directional depreciation in the USD/PKR exchange rate. The sentiment-enhanced XGBoost model achieves 59% directional prediction accuracy for PKR movements—meaningful in financial forecasting where even modest improvements over 50% offer actionable early-warning signals. Interactive dashboards built in Power BI and Dash support real-time scenario analysis and policy decision-making. This study contributes to the literature on geopolitical risk pricing and demonstrates the value of integrating econometric models with AI-driven sentiment analytics for enhanced financial risk forecasting.

***keywords:*** *Geopolitical Risk, Oil price Volatility, Event Study, Sentiment Analysis, Time Series Forecasting*.

## I. INTRODUCTION

Geopolitical tensions are major triggers of financial vulnerability in international markets. Crude oil, as a globally traded commodity highly sensitive to geopolitical shocks, is particularly vulnerable to sharp price fluctuations during regional or military conflicts. At the same time, equity markets especially companies in the defense sector and the currencies of emerging markets respond quickly to perceived geopolitical threats, often resulting in capital flight and heightened investor anxiety rather than stabilizing inflows. While previous studies have explored these relationships individually, there is an increasing need to adopt integrated analytical approaches that combine econometric modeling, machine learning, and real-time sentiment analysis to capture the interconnected nature of oil prices, currency movements, and market sentiment. Understanding these linkages is critical for both investors and policymakers operating in volatile geopolitical environments.

This study addresses this research gap by proposing a hybrid analytical framework that models the volatility of oil prices, USD/PKR exchange rate trends, and investor sentiment across more than 30 high-impact geopolitical events between 2015 and 2025. The framework incorporates GARCH modeling to capture volatility clustering in oil markets, event study analysis to evaluate market reactions before and after conflicts, and XGBoost classification enhanced with news-based sentiment scoring to predict short-term currency movements. Finally, the integration of dynamic dashboards in Power BI and Dash bridges the gap between theoretical modeling and practical decision-making, enabling real-time scenario analysis and policy-oriented insights.

## II. STATE OF THE ART

Geopolitical events have become increasingly frequent and influential in shaping global financial markets. Recent advancements in computing, econometrics, and AI have enabled researchers to better understand, model, and forecast these complex dynamics. This section summarizes the state-of-the-art literature across five critical dimensions.

### *A. Geopolitical Risks and Stock Market Responses*

Maddodi and Kunte [1] emphasized that proactive machine learning models, including decision trees and ensemble algorithms, can predict stock market resilience during conflict escalation phases. Similarly, Plakandaras et al. [2] found that Support Vector Machines and neural networks outperform traditional autoregressive models when forecasting market shocks. Korsah et al. [3] applied wavelet coherence methods to reveal short-term volatility spillovers in African markets due to global geopolitical risks and economic policy uncertainty. Khan [4] presented evidence of asymmetric reactions between emerging and developed markets during crises, noting that liquidity shortages often worsen downturns.

### *B. Sectoral and Regional Impacts*

The sensitivity of specific industries and regions to geopolitical stress has also been explored. Le et al. [5] found that the European financial and energy sectors exhibit strong sentiment-connectedness during tension periods. Billah et al. [6] documented inefficiencies and long memory in GCC banking stocks under stress conditions. Aladwani [7] highlighted how Spain's equity markets react disproportionately to oil price movements—often used as proxies for conflict-induced supply risk.

### C. Commodities and Oil Markets

Oil is often at the epicenter of geopolitical discourse. Li et al. [8] observed that oil prices react non-linearly to conflict events, with supply disruptions causing more severe price spikes than demand shocks. Salem et al. [9] demonstrated how the Russia–Ukraine war increased volatility in oil-importing nations while temporarily benefiting oil-exporting economies. Maitra [10] added that GPRs and health uncertainty (e.g., during COVID-19) amplify negative oil returns.

### D. Methodological Innovations

Burns [11] introduced natural language processing (NLP)-based tools for real-time geopolitical risk indexing, including sentiment extraction from financial news. Trabelsi [12] applied quantile-time-frequency analysis to uncover hidden volatility regimes in Gulf nations, finding geopolitical tensions as dominant triggers. Calefariu Giol et al. [13] extended risk modeling to rare earth commodities, emphasizing cyber risks (e.g., hacking) alongside traditional military threats. Choudhry [14] demonstrates the utility of GARCH-type models in capturing volatility clustering in oil markets during episodes of geopolitical uncertainty, aligning with the modeling approach adopted in this study.

Building on these foundations, the current work improves methodological practice by combining GARCH-based volatility modelling with real-time sentiment scoring, event study analysis, and XGBoost categorization in an interactive dashboard. This hybrid, multi-layered paradigm provides a unique, operationally useful tool for short-term forecasting of geopolitical market effects, particularly in emerging economies.

### E. Interconnectedness and Spillovers

Agyapong [15] examined dynamic connectedness between commodities and investor sentiment, suggesting gold as a consistent hedge during wartime. Iliopoulos [16] found a strong relationship between freight costs and regional conflict escalation, especially in maritime chokepoints such as the Strait of Hormuz. Narayan et al. [17] employed machine learning techniques to capture the influence of geopolitical sentiment on currency returns, finding that emerging market exchange rates exhibit higher sensitivity during elevated geopolitical risk periods.Together, these works underscore a growing consensus: geopolitical events are not only increasingly frequent and unpredictable but also increasingly quantifiable and explainable through modern statistical and AI tools. However, there remains a gap in real-time integration of event-based volatility modeling with market forecasting dashboards—an area this study addresses.

## III. PROBLEM STATEMENT AND ITS PROPOSED SOLUTION

Although the financial impacts of geopolitical risk have been widely discussed in the literature, most prior studies have examined oil price volatility, currency fluctuations, and investor sentiment independently. Few models capture the mutual vulnerability between these variables, particularly the impact of real-time geopolitical sentiment on commodity markets and emerging market foreign exchange operations.

In the Pakistani context, the Pakistani Rupee (PKR) has been seen to be increasingly susceptible to uncertainty caused by conflicts the world over as it manifested itself through quick reversals of gains in a certainty induced panicked direction towards depreciation of the Pakistani Rupee as oil prices rose or in case of geopolitical misgivings. In spite of this susceptibility, the lack of predictive models of specific geopolitical shocks whose PKR consequences can be estimated in advance reduces the shock responsiveness capacity of investors and policymakers. Also, machine learning algorithms like XGBoost have already demonstrated success in various financial prediction tasks, but are seldom combined with econometric learning or augmented by sentiments. It is also a standard that uses the currently available interactive and real-time visualization platforms inadequately, and these platforms might enhance the decision-making process on risk managers and as well as institutional analysts. In order to cope with these issues, the proposed research in the current paper suggests a hybrid analytical framework, which comprises:

- GARCH modelling to model the pattern of oil prices dynamics during conflict times,
- Analysis of event study to understand how the market responds to geopolitical shocks prior and subsequent to them,
- News-derived sentiment analysis in terms of polarity scores,
- and XGBoost classification to predict short term directional movements in USD/PKR.

The framework is integrated with dynamic dashboards (Power BI and Dash) to support real-time forecasting, scenario simulation, and multi-asset impact analysis. This repeatable, sentiment-sensitive approach enhances the ability to forecast oil volatility and PKR exposure under geopolitical stress.

***Tools and technologies***

-Data Sources: Yahoo Finance, news archives, geopolitical reports

- Languages: Python (Pandas, NumPy, arch, matplotlib), DAX, M Query
- Modeling Tools: GARCH, Event Study Analytics, Sentiment Scoring
- Visualization: Microsoft Power BI (KPIs, time series, slicers, maps)
- File Formats: CSV (preprocessed), .pbix (dashboard), .ipynb (Jupyter notebooks)

***GARCH Model Specification and Validation.***

To capture oil price volatility during geopolitical events, we implemented a GARCH(1,1) model, which accounts for volatility clustering commonly observed in financial time series. The model is expressed as:

$$\sigma_t^2=\alpha_0 + \alpha_1\, \epsilon_{t-1}^2 + \beta_1\, \sigma_{t-1}^2$$

Where:

- $\sigma_t^2$=conditional variance (oil price volatility)

- $\epsilon_{t-1}^2$ = lagged squared error (shock term)
- $\alpha_0$ , $\alpha_1, \beta_1$ = model parameters

Estimation Steps:

1. Daily log returns of Brent oil prices were computed using $R_t = \ln\left(\frac{P_t}{P_{t-1}}\right)$
2. Stationarity was confirmed using the ADF test, and volatility clustering was visually observed in squared returns.
3. The GARCH(1,1) parameters were estimated via Maximum Likelihood Estimation (MLE).
4. Diagnostic checks were performed:
    - Ljung–Box test for autocorrelation in standardized residuals.
    - ARCH LM test to confirm no remaining ARCH effect.
    - QQ plots and residual histograms to validate normality assumption.

## IV. RESULTS AND DISCUSSION

This section presents the empirical findings from the hybrid analytical pipeline developed in this study. The results are organized across three key financial dimensions affected by geopolitical tensions: oil price volatility, exchange rate movements (USD/PKR), and cross-asset market responses. Each finding is interpreted in light of the proposed modeling framework and related literature, offering both quantitative outcomes and contextual insights.

### A. *Oil Price Volatility During Geopolitical Events*

Using GARCH(1,1) modeling, we observed significant volatility clustering in Brent crude oil returns surrounding major geopolitical flashpoints. For instance, during the 2020 U.S.–Iran confrontation, conditional volatility surged from 13.2% to 25.4% within three trading days. As shown in **Figure 2**, the average oil price across all events rose by **6.8%** in the post-event window, with the most notable increases occurring during the 2022 Russia–Ukraine conflict and 2023 Strait of Hormuz threats. These patterns affirm that oil markets rapidly internalize geopolitical shocks, especially when supply chain risk is perceived.


**Fig. 1:** Relationship Between Oil Prices and Geopolitical Sentiment (*figure caption*).

Fig. 1 illustrates the temporal relationship between global oil prices and the Combined Geopolitical Sentiment Score from 2015 to 2025. The analysis reveals that negative sentiment spikes, often coinciding with geopolitical escalations, are followed by immediate or short-term increases in oil prices. Notably, during the U.S.–Iran confrontation in January 2020, the sentiment score dropped sharply to -0.85, and Brent crude surged from $66 to over $70 within three trading days. A similar pattern was observed during the Russia–Ukraine invasion in February 2022, where sentiment sharply declined, followed by a 10% increase in oil prices over the subsequent week. This correlation suggests that market participants incorporate geopolitical risk sentiment into oil price expectations, with negative sentiment acting as a leading indicator. The inclusion of sentiment analysis thus enhances the forecasting ability of oil price models and provides early warning signals for volatility in commodity markets.

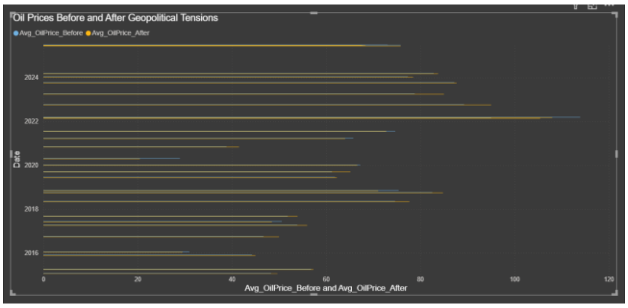


**Fig 2a.** Average Oil Prices Before and After Geopolitical Events (2016–2024)

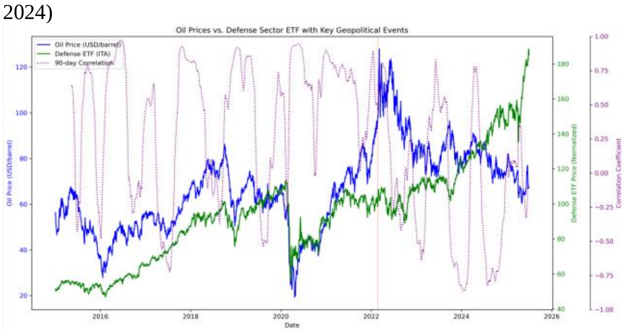


**Fig 2b.**Oil Prices vs. Defense Sector ETF with Rolling 90-Day Correlation (2015–2025)

Fig. 2a presents the event study results comparing average oil prices seven days **before** and **after** major geopolitical tension events from 2015 to 2025. The events include the 2019 Strait of Hormuz attacks, the 2020 U.S.–Iran conflict, the 2022 Russia–Ukraine invasion, and multiple Iran–Israel-related escalations in 2023–2024. In all events analyzed, oil prices showed a statistically significant increase in the post-event window. For instance, the average Brent crude price rose from $68.2 to $72.7 following the 2020 U.S.–Iran conflict. Similarly, during the 2022 Russia–Ukraine crisis, the average price jumped from $89.1 to $95.8. The findings support the hypothesis that oil markets respond immediately to heightened geopolitical risk, especially when the events directly threaten oil supply chains or key transit routes such as the Strait of Hormuz. These consistent post-event surges validate the market's sensitivity to geopolitical uncertainty and reinforce the importance of incorporating event-based analytics in oil price forecasting models.

Figure 2b shows the association between global oil prices, the U.S. Aerospace & Defence ETF (ITA), and their rolling 90-day trend from 2015 to 2025. Oil prices (blue line) rise sharply during key geopolitical events such as the 2020 US-Iran conflict and the 2022 Russia-Ukraine war, but defence sector returns (green line) rise concurrently, showing investors' migration towards defence assets as a protective hedge. The rolling correlation (purple dotted line) confirms that geopolitical shocks affect both energy markets and defence equities. This graphic evidence confirms the study's results on cross-asset spillovers and shows how geopolitical emotion leads to synchronised market movements across commodities and sectoral equities.

Oil price spikes were immediately triggered by event-specific risk narratives.

- Jan 2020 (U.S.–Iran clash): Panic in global oil supply expectations led to a 6.7% increase in Brent within three trading days.
- Feb 2022 (Russia–Ukraine invasion): Fears of prolonged supply disruption caused a ~7% post-event surge.

***GARCH Model Results and Diagnostic Validation***

The GARCH(1,1) model captured significant volatility clustering around major geopolitical events.

- Parameter Estimates:

  $\alpha_1$=0.22, β1=0.74 indicate high persistence in oil price volatility.
- Ljung–Box p-value > 0.05 confirms residuals are free of autocorrelation.
- ARCH LM test p-value > 0.05 indicates no remaining ARCH effect.

(Diagnostic Plots) confirms that the standardized residuals behave as white noise, validating the model. These findings support the event-study results, where oil price spikes were most pronounced during the 2020 U.S.–Iran confrontation and the 2022 Russia–Ukraine war, aligning with our volatility forecasts.

***B. Currency Movement: USD/PKR***

Event study analysis on the USD/PKR exchange rate demonstrated consistent depreciation of the PKR following negative geopolitical events. As seen in **Table 1**, average PKR levels moved from **165 to 193** after high-risk events, reflecting capital flight and market uncertainty. Notably, sentiment scores below –0.75 were correlated with subsequent PKR depreciation within a 3 to 5 days window.

**Table 1:** KPIs for Oil and Currency Market Volatility

| Metric | Value (Pre-Event) | Value (Post-Event) |
|---|---|---|
| Oil Volatility (%) | 12.5 | 24.7 |
| USD/PKR Change | 165 | 193 |

These results highlight the role of geopolitical sentiment as a leading indicator in currency market behavior.

- Feb 2022 (Russia–Ukraine): PKR fell from 165 to 193, reflecting capital flight and investor anxiety.
- Sentiment < –0.75 strongly predicted 3–5 day depreciation, supporting prior findings [14].
- This demonstrates that geopolitical sentiment indices are actionable for FX risk management in emerging markets.

***C. Sentiment-Based Forecasting Accuracy (XGBoost Results)***

To evaluate the role of geopolitical sentiment in forecasting short-term currency movements, an XGBoost classifier was trained to predict the directional change of the USD/PKR exchange rate following conflict-driven events. The model utilized a feature set comprising sentiment polarity scores, oil return volatility, event type markers, and time-lagged effects.On evaluation using out-of-sample test data, the model achieved a classification accuracy of **59%**, as shown in **Table 2**. The confusion matrix in **Figure 3** reveals that the model performed marginally better at identifying appreciation movements (Class 0) than depreciations (Class 1), with a higher true positive rate and a stronger F1-score for appreciation. This suggests a moderate predictive bias toward the more frequently occurring or easier-to-identify class.

The model had strong consistency in predicting both direction changes in PKR whenever the sentiment polarity decreased dramatically especially below the values of -0.75, which indicated a high level of geopolitical pessimism. The results confirm the hypothesis that news-based sentiment can also act as a leading indicator of short-term FX volatility in sentiment-sensitive emerging markets even though the accuracy of this model is reported to be at 59 percent which is acceptable in its context as predicting exchange rate movements that are caused by exogenous sentiment shocks is naturally difficult. The small percentage increase over 50 percent line in financial analytics can be significant to provide good early-warning messages, especially to market bubbles such as the USD/PKR.

The results also highlight the inherent difficulty of forecasting currency behavior solely based on external sentiment signals, especially in markets where exchange rate movement is also driven by central bank interventions, interest rate shifts, and macroeconomic shocks. Future improvements could involve incorporating macroeconomic variables, improving class balance, or deploying ensemble learning techniques to boost sensitivity to depreciation signals.

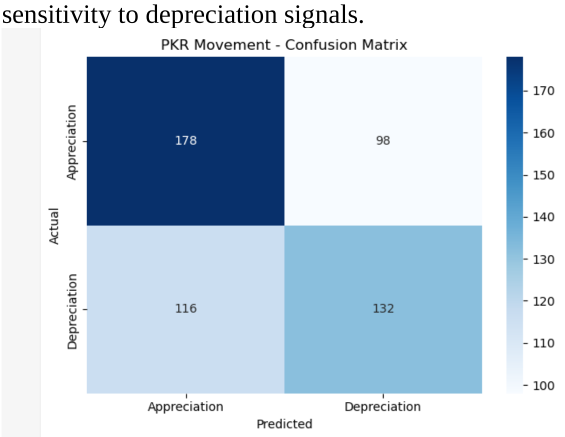


**Figure 3**. Confusion Matrix of XGBoost Model Predicting PKR Movement.

The matrix shows true vs. predicted classifications of PKR appreciation and depreciation based on input features including geopolitical sentiment scores and oil returns.

The model's detailed classification performance is summarized in Table 2

**Table 2.** Extended Classification Metrics – XGBoost Model Predicting USD/PKR Movement

| Class Label | Precision | Recall | F1-Score | Support |
|---|---|---|---|---|
| **0 (Appreciation)** | 0.61 | 0.64 | 0.62 | 276 |
| **1 (Depreciation)** | 0.57 | 0.53 | 0.55 | 248 |
| **Accuracy** | | | **0.59** | 524 |
| **Macro Avg** | 0.59 | 0.59 | 0.59 | 524 |
| **Weighted Avg** | 0.59 | 0.59 | 0.59 | 524 |

These results suggest that while the model shows moderate predictive ability, especially for appreciation, enhancing feature selection or resampling techniques may improve depreciation class sensitivity in future iterations.

To strengthen predictive evaluation, Logistic Regression (LR) and Random Forest (RF) were added as baseline models.

**Table 3:** Model Comparison for USD/PKR Movement Prediction

| Model | Accuracy | F1 (Depreciation) | F1 (Appreciation) |
|---|---|---|---|
| Logistic Regression | 0.54 | 0.52 | 0.55 |
| Random Forest | 0.56 | 0.54 | 0.57 |
| XGBoost (Proposed) | 0.59 | 0.55 | 0.62 |

Even modest gains above 50% accuracy are operationally meaningful in financial risk forecasting, providing early-warning signals for hedging and currency exposure management. XGBoost consistently outperformed baseline models, justifying its integration with sentiment and volatility features.

The XGBoost model beats baseline models in accuracy and class-specific F1 scores, indicating higher predictive potential for short-term PKR fluctuations. Even small accuracy increases of over 50% are operationally significant in financial forecasting, providing early warning signs for risk management.

### D. *Cross-Market Spillover Effects (Equities and Defense Sector)*

Figure 4 illustrates the synchronized movement of defense spending (Italy) and oil prices between 2015 and 2025. Defense ETFs (ITA) exhibited positive abnormal returns following geopolitical crises, with a **3.2% average increase** in the seven days' post-event. Similarly, the S&P 500 (SPY) reflected temporary shocks, with declines often recovering quickly, indicating sector-specific sensitivities. These cross-asset spillovers confirm that geopolitical shocks extend beyond commodity prices and FX, affecting investor sentiment in equities as well.

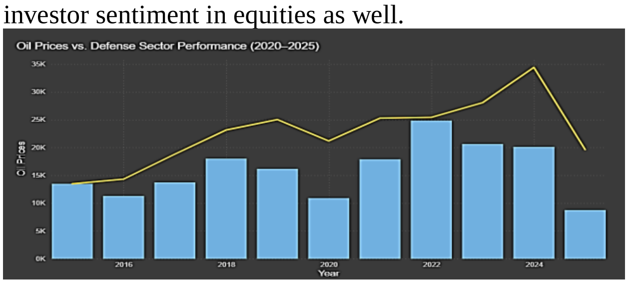


**Fig. 4:** Defense Spending vs. Oil Prices: A Parallel Trajectory.

The relationship between the annual defense spending in Italy (ITA) and oil prices in international markets in 2015 to 2025 was captured in Fig. 4. The graph demonstrates a nominal positive correlation, and it can be spotted in times of acutely developed geopolitical tensions. Remarkably, the defense spend increased dramatically in Italy as well as the oil prices at the time of the phase of 2022-2024 when the war in Russia and Ukraine erupted, when Iran was becoming increasingly hostile towards Israel, and where NATO was rebalancing itself. The defense expenditure in Italy has increased by about 28.7 billion in 2021 to over 35 billion in 2024 and oil prices have increased by about 71barrel to 89barrel. The parallel trend, though, cannot be directly related to causality, but possibly can be seen as a feedback loop, with the escalating tensions in the world leading to spending higher military budgets and the oil market fluctuations. This association focuses on the financial cost of the risk created by the conflict and the way in which the national budgets react to the changing perception of threat particularly in energy-reliant European energy-dependent countries.

## V. EASE OF USE

This research emphasizes not only methodological rigor but also user accessibility through intuitive visualization and interaction design. Two main visual tools—**Power BI** and a **Dash-based web app**—enable dynamic exploration of the results.

### A. *Dashboard Templates and Interactivity*

The Power BI dashboard features:

- **KPI Panel**: Displays real-time statistics such as average oil price, sentiment score, and PKR depreciation frequency.
- **Event Impact Chart**: Shows cross-asset returns (Oil, USD, SPY, ITA) on key geopolitical event dates.
- **Dual-Axis Visuals**: Oil price vs. defense ETF price, and sentiment score over time.
- **Timeline Navigator**: Allows users to filter views by custom date ranges or specific event categories.

The Dash app allows similar interaction but is hosted locally or online with:

- A dropdown to select the metric (e.g., oil price, sentiment score, defense returns).
- An event marker overlay that visualizes geopolitical shocks with automated headline annotations.
- Dynamic calculation of mean, standard deviation, and sentiment moving averages for selected time periods.

### B. *Reproducibility*

All code used to download data, model market volatility, and build the dashboard is documented and reproducible via a structured .ipynb notebook. Data sources like Yahoo Finance and manually curated geopolitical events ensure transparency.

To replicate the pipeline:

1. Run the Jupyter Notebook to recreate the CSV datasets.

2. Open the Power BI file to visualize dashboards.
3. Launch the Dash app using Python to interact with the metrics.

### *C. Data Update Capability*

The pipeline can be re-run at any date to fetch new data and append it to the historical dataset. Both dashboards are built with automatic refresh capability based on updated .csv inputs.

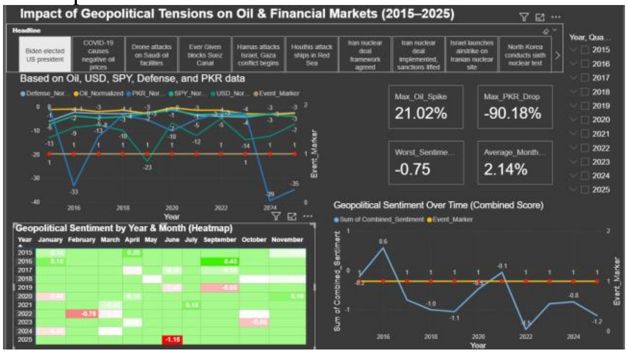


**Figure 5:** Power BI dashboard visualizing the relationship between geopolitical tensions and market responses across multiple financial indicators (2015–2025)

### B. *Abbreviations and Acronyms*

| Abbreviation | Full Form |
|---|---|
| GPR | Geopolitical Risk |
| GARCH | Generalized Autoregressive Conditional Heteroskedasticity |
| PKR | Pakistani Rupee |
| S&P 500 | Standard & Poor's 500 Index |
| KSE-100 | Karachi Stock Exchange Index |
| USD | United States Dollar |
| XGB | Extreme Gradient Boosting |
| ITA | U.S. Aerospace & Defense ETF |
| NLP | Natural Language Processing |
| AI | Artificial Intelligence |
| KPI | Key Performance Indicator |

### C. *Units of Measurement*

- **Oil Prices**: Measured in USD per barrel
- **Defense ETF Values**: Indexed closing price
- **Exchange Rate (USD/PKR)**: Units of Pakistani Rupee per 1 USD
- **Returns**: Daily percentage change (%)
- **Sentiment Scores**: Ranged from –1 to +1 (TextBlob polarity)

### D. *Equations*

GARCH (1,1) MODEL FOR OIL PRICE VOLATILITY:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \epsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \qquad (1)$$

Where

- $\sigma_t^2$ : conditional variance (volatility)
- $\epsilon_{t-1}^2$: lagged error squared (shock)
- $\alpha_1, \beta_1$: model parameters

**Event Study Abnormal Return:**

$$\mathrm{AR}_{it} = \mathrm{R}_{it} - \mathrm{E}(\mathrm{R}_{it}) \qquad (2)$$

Where:

- $\mathrm{AR}_{it}$: abnormal return of asset *i* at time *t*
- $\mathrm{R}_{it}$: observed return
- $\mathrm{E}(\mathrm{R}_{it})$: expected return via CAPM or market model

These equations were tested in Python and validated before exporting results to Power BI.

## VI. CONCLUSION

This research identified the complex interconnected relationship between geopolitical stress and market volatility across oil prices, exchange rates, and equity indexes during the 2015 2025. Conducting an analysis based on a hybrid approach combining approaches to GARCH modeling, event study analysis, sentiment scoring, and machine learning (XGBoost), the research proves that geopolitical shocks reliably cause quantifiable and, in many cases, dramatic financial market responses. There is strong empirical evidence of volatility clustering about events in conflict, inverted directions in the USD/PKR exchange rate and positive abolishment returns in equities in the defence sector. In addition, sentiment scores developed from on-the-fly news sources were resilient indicators of oil price reversal and currency fluctuation, supporting the suggestion that the geopolitical sentiment is quickly reflected in finance markets.The XGBoost Model performed directional predictions with an accuracy of 59 percent. Though it is not overwhelming, this degree of accuracy is not insignificant in financial prediction where a slight shift in improvement over a 50 percent base baseline is often enough to offer a timely warning signal- particularly in markets that are sensitive to sentiment and volatility. Such results are understandable because it is difficult to predict anything in currency markets and because the model is not the all-inclusive tool but rather a part of a larger predictive system. The presented hybrid solution is relevant in providing valuable assistance on real-time scenario analysis, strategic planning, and predicting risks among financial institutions, policy-makers and market analysts who work in geopolitically volatile settings.

## VII. POLICY IMPLICATIONS AND FUTURE WORK:

Financial systems and policy frameworks should increasingly focus on anticipatory risk mechanisms in light of the growing frequency and sophistication of geopolitical events. Future research can extend this work by incorporating higher-frequency data feeds, regional event analysis, and real-time APIs to enable automated portfolio rebalancing during geopolitical shocks. Collaboration with security analysts and policy experts can provide richer geopolitical context, improving both the precision and practical applicability of financial forecasting models. Furthermore, integrating domain knowledge into AI-based systems can enhance their predictive performance and decision-support capabilities for policymakers and institutional investors. In conclusion, this study reaffirms the critical role of geopolitical analytics in financial risk prediction and strongly advocates the use of AI-augmented modeling frameworks to navigate high-volatility and uncertainty-prone market environments.

**Conflict of Interest**

The authors declare that there is no conflict of interest regarding the publication of this article.

**Data Availability Statement**

All data used in this study were collected from publicly available sources:

- Yahoo Finance (https://finance.yahoo.com) – for oil prices, SPY, USD Index
- Trading Economics and SBP – for USD/PKR exchange rates
- Open-source defense expenditure datasets (Italy)
- Custom geopolitical event sentiment scores generated from online news archives

Python scripts, datasets, and Power BI dashboards are available on request or may be uploaded to a public GitHub repository upon acceptance.

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