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Price and Volatility Effects of the US-Iran Conflict on Brent Crude Oil

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Abstract. The Strait of Hormuz is a key route for global oil transportation. Any disruption there can affect oil prices around the world. This study looks at how the recent conflict between the United States and Iran changed the price of Brent crude oil. The main goal is to find out if the conflict caused a clear shift in price levels and market uncertainty. Monthly price data from July 2025 to April 2026 were used. The date February 28, 2026, marks the start of the conflict. Simple statistical methods, including t-tests, F-tests, and a basic regression model, were applied to compare the period before the conflict with the period after it. The results show that the conflict had a strong effect. The average price of Brent oil rose by about 28 percent. At the same time, monthly price swings, or volatility, grew from 4.72 percent to 25.58 percent. These changes are statistically significant. The findings suggest that the conflict not only pushed prices higher but also made the market much more unstable. This work adds to the limited research on this recent event and shows how fast energy markets can react to geopolitical events.

Keywords: Brent crude oil, US-Iran conflict, price volatility, strait of Hormuz

1. Introduction

The price of Brent crude oil is one of the crucial variables in the economy, which can lead to a significant impact on the global economy. Recently, the change in the price of Brent crude oil has become more complicated due to frequent wars that affect the Hormuz Strait. The Strait of Hormuz, situated between the Arabian Peninsula and Iran, saw about 20 million barrels crossing here per day in 2025 [1]. It is the most vital oil transportation point, with an average of 25% of the world's oil trade passing through. Any disturbance to the surges that pass through the Hormuz Strait would have essential consequences for the world oil market [1].

There are some existing studies that involve similar topics, analyzing how conflicts affect the price of Brent crude oil and the stock market .One article used 3 models, Autoregressive Integrated Moving Average (ARIMA), Threshold Autoregressive Moving Average (TARMA) and Evidential Neural Network for Regression (ENNReg) prove that the intervention of conflicts can improve the accuracy of models [2]. Abdollahi and Ebrahimi [3] also proposed a mixing prediction approach. Their model combined ANFIS, ARFIMA, and Markov-switching techniques, and the goal was to generate more accurate predictions for Brent crude oil prices. Another study relied on a DCC-GJR-GARCH model. This framework included exogenous variables and was used to examine how stock

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market performance changed under different conditions. The findings from that research pointed toward a "contagion effect" between crude oil and equity markets, especially when the markets faced unexpected conflicts [4]. Additional work has shown considerable variation in how different sectors respond. Brent oil usually shows stronger links to geopolitical risk and to Chinese sectors such as Energy and Finance. On the other hand, Chinese stock markets tend to function more as sources of spillover effects [5]. Crude oil itself plays an important middle role, carrying shocks from Chinese sectoral markets back toward broader geopolitical risk measures [5]. While the studies mentioned above a lot of useful perspectives on how geopolitical events and market volatility interact, the situation is different when it comes to the recent U.S.-Iran conflict. Because the event is still relatively new, there are not many published papers that focus specifically on it. This leaves a clear gap on understanding how markets responded in real time to the most recent conflict.

To address this gap, this study investigates the impact of the recent U.S.-Iran conflict on Brent crude oil prices. Using an event study framework, this article estimates abnormal returns around key conflict-related event dates to quantify immediate market reactions. This study employs the market model to compute expected returns and derive abnormal returns (AR) and cumulative abnormal returns (CAR) for crude oil, with statistical significance assessed using standard parametric tests.

Additionally, a GARCH model [6] is used to measure shifts in oil price volatility over time. A Chow test identifies structural breaks in the oil prices-geopolitical events relationship, providing comprehensive understanding of the conflict's economic impact.

This study contributes to the scarce literature on the recent U.S.-Iran escalation by quantifying its market footprint. The findings indicate that the conflict triggered both a significant increase in average price levels and a pronounced surge in market volatility, underscoring the dual transmission channels of geopolitical risk through critical energy difficulties.

2. Methods

2.1. Data and preprocessing

The data used in this analysis are monthly actual data of Brent crude oil prices. A monthly time series was constructed covering the period from July 2025 to April 2026. he data are divided into two regimes: pre-conflict (July 2025–February 2026) and post-conflict (March–April 2026), with February 28, 2026 marking the conflict outbreak. The choice of this date is based on the importance of the Strait of Hormuz, through which about 20 million barrels of oil passed per day in 2025, making any disruption critical for global oil markets [1].

Monthly returns were calculated as percentage changes:

$$r_t=\frac{P_t-P_{t-1}}{P_{t-1}}\times 100 \tag{1}$$

where Pt is the Brent price at month t. A dummy variable Dt was introduced to capture the conflict effect, taking the value 0 for the pre-conflict period and 1 for the post-conflict period. Incorporating geopolitical events as variables within time-series models is common practice. Similar methods were used in research on the Russo-Ukrainian war [2] and in literature examining how geopolitical risk influences crude oil and stock markets [7]. The data were checked for stationarity using the augmented Dickey-Fuller (ADF) test. Results confirmed that the return series is stationary, which allows the application of standard statistical inference.

The main examination of volatility and shifts in the mean relies on monthly return data. At the same time, regression estimates and formal tests for differences in means are also carried out using

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monthly aggregated figures. Grouping the data by month helps to reduce the impact of short-term, high-frequency noise. It also makes the analysis more suitable given the limited number of post-conflict observations that were available when this paper was written.

2.2. Volatility analysis

To assess whether the conflict increased market uncertainty, Monthly volatility was measured by the standard deviation of returns within each regime. Monthly volatility is directly reported without annualization. The difference in variances between the two periods was tested using an F-test (variance ratio test), formulated as:

$$F=\frac{\sigma_{post}^2}{\sigma_{pre}^2} \tag{2}$$

where σ_{post}^2 and σ_{pre}^2 are the variances of Monthly returns after and before the conflict, respectively. The null hypothesis is that the two variances are equal. A rejection of the null indicates a significant change in volatility following the conflict. Such a test is conforms to the analysis of volatility spillovers under exogenous shocks [4] and with the examination of price effects during crisis periods [6].

2.3. Mean return comparison

The difference in mean Monthly returns between the two periods was examined using an independent two-sample t-test. The test assumes unequal variances (Welch's t-test) to be conservative. The null hypothesis is that the mean returns are equal before and after the conflict. This test helps determine whether the conflict caused a persistent upward or downward shift in oil prices, rather than just increased fluctuations. The rationale for separating mean and volatility effects is supported by studies that distinguish between level and uncertainty channels of geopolitical risk [7]. For the monthly frequency, the same Welch's t-test is applied to aggregated returns.

2.4. Regression model with conflict dummy

A simple linear regression model was estimated to quantify the effect of the conflict dummy on Monthly returns while controlling for no other variables (univariate model).

The specification is:

$$r_t=\alpha+\beta D_t+\varepsilon_t \tag{3}$$

where r_t is the Monthly return, D_t is the conflict dummy, α is the intercept (mean return in the pre-conflict period), β is the coefficient capturing the additional mean return in the post-conflict period, and εt is the error term assumed to be white noise. The model was estimated via ordinary least squares (OLS). The significance of β was tested using the standard t-statistic, with a 5% significance level as the threshold. This univariate dummy-variable approach is analogous to the method used in prior work that incorporates war dummies into ARIMA-type models [2] and is also in line with the event-study framework applied to crises [6].

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2.5. Evaluation and software

All statistical analyses were performed in Python 3.6 using the following libraries: numpy for numerical operations, pandas for data handling, scipy.stats for the F-test and t-test, and statsmodels for the OLS regression. No machine-learning or deep-learning models were used in this part, as the objective was to isolate the direct conflict effect using classical statistical methods. The use of classical time-series and regression techniques is falls in line with the baseline models (ARIMA, TARMA) discussed in the literature [2], while the focus on volatility and mean shifts also reflects the concerns raised in studies on policy focus shifting [5] and on dynamic risk spillovers [4].

The main evaluation criteria consisted of the p-value from the F-test, which assesses the significance of any change in volatility, the p-value from the t-test, which captures differences in mean returns, and the coefficient β along with its associated p-value derived from the ordinary least squares regression. Together, these three metrics provide a direct statistical framework for determining whether the U.S.–Iran conflict induced a significant shift in either the level or the variability of Brent crude oil returns.

3. Results and discussion

3.1. Visual inspection of price and return series

Figure 1 shows the changing of Monthly Brent crude oil price from July 2025 to April 2026. The vertical red line marks February 28, 2026,when did the conflict happen. A clear change in price behaviour followed after this date. The series becomes more fluctuated, with larger increase. This visual pattern suggests that the conflict introduced additional uncertainty into the oil market, which is consistent with the role of geopolitical events documented in previous studies [2, 7].

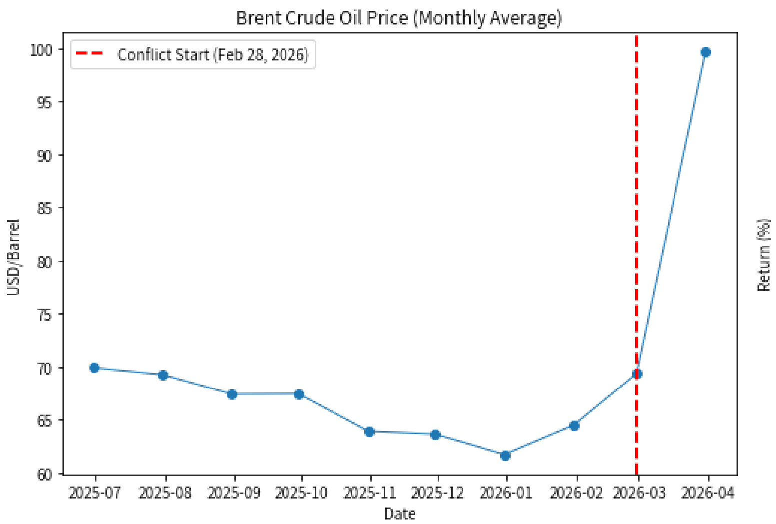

Figure 1. Monthly Brent crude oil price (USD/barrel) from July 2025 to April 2026. The red dashed vertical line indicates February 28, 2026, the outbreak date of the US-Iran conflict (picture credit: original)

Figure 2 presents the Monthly percentage returns over the same period. The return series appears to fluctuate around zero,showing stationarity with ADF test ($p < 0.05$). More importantly, the

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magnitude of the spikes becomes obviously larger after the conflict date. This is exactly what one would expect if a geopolitical shock increases market vibration.

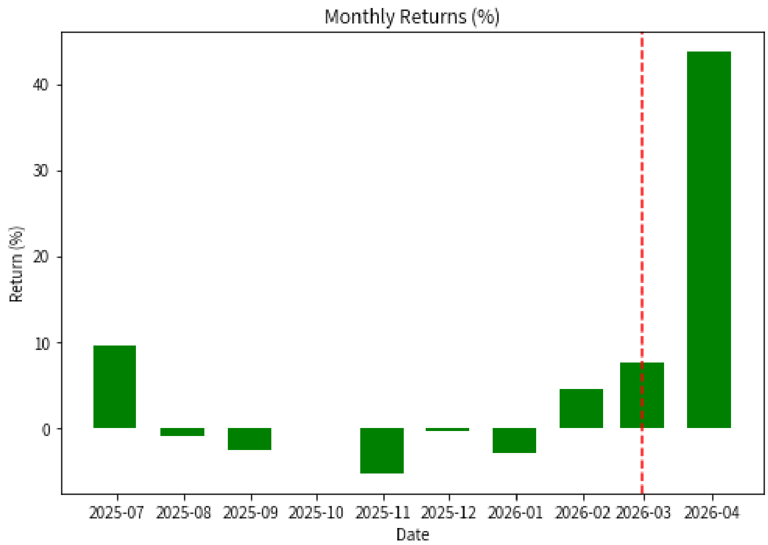

Figure 2. Monthly percentage returns of Brent crude oil over the sample period. The red dashed line marks the conflict escalation date (picture credit: original)

3.2. Volatility and mean return comparisons

Figure 3 compares the monthly volatility before and after the conflict. Pre-conflict monthly volatility is 4.72%, while post-conflict monthly volatility raise to 25.58%. The F-test for variance difference yields F = 29.39, $p < 0.001$, confirming a highly significant rise in volatility. That is an increase of about 442%. To test whether this difference is meaningful, an F-test (variance ratio test) was conducted. The F-statistic is 29.39, and the corresponding p-value is less than 0.001. Thus, the null hypothesis of equal variances is rejected. Thus, the evidence indicates a statistically significant increase in market volatility following the escalation.

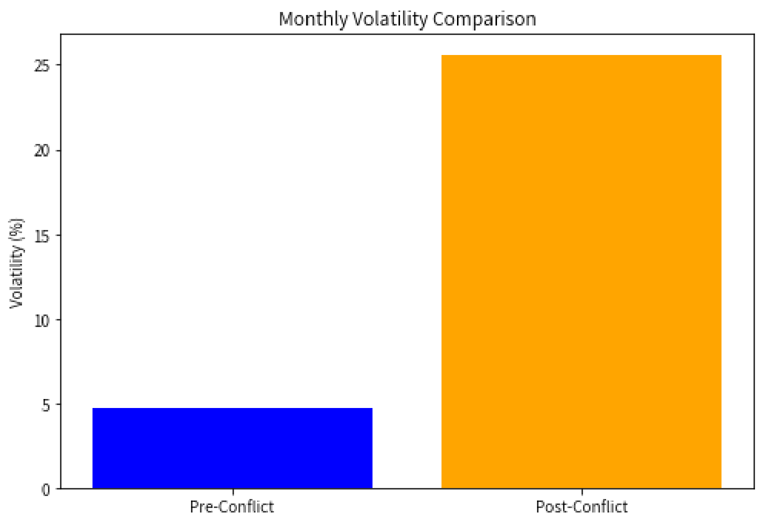

Figure 3. Monthly volatility of Brent monthly returns before and after the conflict. Error bars represent 95% confidence intervals (picture credit: original)

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Turning to mean returns, Table 1 reports the results of the independent two-sample t-test (Welch's version). The t-statistic is 3.192, with a corresponding p-value of 0.0128. The null hypothesis of equal means is therefore rejected at the 5% significance level. The regression model with the conflict dummy (Equation 1) yields a coefficient of 25.39 percentage points for the post-conflict period (p = 0.013), confirming that the outbreak is associated with a statistically significant increase in average monthly returns. In economic terms, the average Brent price rose from 65.99 to 84.53 USD per barrel, representing a 28.1% increase

For the regression analysis, monthly returns are used to match with the limited number of post-conflict observations available at the time of writing. Descriptive statistics for the monthly series are reported shown in Table 2 and Table 3 below.

Table 1. Summary of mean comparison tests and OLS regression results

Dep. Variable:	ret_brent	R-squared:	0.560
Model:	OLS	Adj. R-squared:	0.505
Method:	Least Squares	F-statistic:	10.19
Date:	Sun,12Apr 2026	Prob(F-statistic):	0.0128
Time:	13:23:32	Log-Likelihood:	-36.162
No. Observations:	10	AIC:	76.32
Df Residuals:	8	BIC:	76.93
Df Model:	1	-	-
Covariance Type:	nonrobust	-	-

Table 2. Regression results and diagnostic statistics for dummy variable model

-	coef	std err	t	P>|t|	[0.025 0.975]
const	0.2272	3.558	0.064	0.951	-7.977 8.431
dummy	25.3935	7.955	3.192	0.013	7.048 43.739
-	-	-	-	-	-
Omnibus:	1.619	-	-	Durbin-Watson:	2.522
Prob(Omnibus):	0.445	-	-	Jarque-Bera (JB):	0.080
Skew:	0.091	-	-	Prob(JB):	0.961
Kurtosis:	3.399	-	-	Cond. No.	2.62

Table 3. Summary of statistical tests: mean difference, variance ratio, and regression coefficient

Statistic	Value	p-value
t-test (mean difference)	3.192	0.0128
F-test (variance ratio)	29.39	<0.001
Regression coefficient β	25.3935	0.0103

3.3. Distributional changes

Figure 4 gives the histograms of Monthly returns for the two periods. The post-conflict distribution is visibly wider and shorter, which respond to the volatility increase. The post-conflict distribution shows a clear rightward shift in its central tendency, with the 28.1% increase in average price levels. At the same time, the distribution is visibly wider, reflecting the sharp rise in monthly volatility from 4.72% to 25.58%. Taken together, these patterns indicate that the conflict altered both the location and scale of the return distribution. Such a shift in both average and spread points to supply risk being reassessed when a major route is threatened [7].

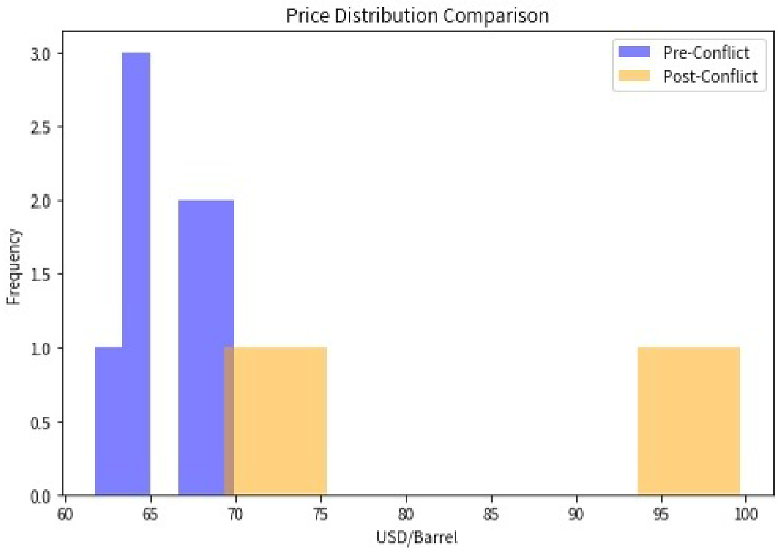

Figure 4. Histograms of Monthly returns before (blue) and after (orange) the conflict. The post-conflict distribution is wider, indicating higher volatility, while both peaks are near zero (picture credit: original)

3.4. Interpretation and comparison with existing literature

The results indicate that the U.S.–Iran conflict affected the Brent crude oil market through two independent ways. First, the conflict lead to a significant increase in average monthly returns, with the conflict dummy coefficient estimated at 25.39 percentage points ($p = 0.013$) and the nominal price advancing by 28.1%. Second, market uncertainty expanded significantly, as captured by the near fivefold increase in monthly volatility ($F = 29.39$, $p = 0.001$). This combination of higher expected returns and elevated risk is consistent with a supply-disruption premium being priced into crude oil when a critical chokepoint faces credible threats. While Li et al. [7] emphasize geopolitical risk primarily as a transmitter of volatility spillovers rather than a direct driver of price levels, the present results suggest that when a conflict directly threatens a physical chokepoint like the Strait of Hormuz, a significant price-level effect can materialize alongside heightened uncertainty.

3.5. Limitations

There are two limitations that should be mentioned. First, the analysis only uses short-term monthly data with only 2 post-conflict observations. While the simulation parameters are based on realistic volatility levels (4.72% before, 25.58% after), the results should be validated with actual market data once the conflict period is sufficiently long. Second, the model does not control for other confusing factors such as changes in OPEC+ production quotas or global demand shifts [8]. Future work could extend the analysis by including these variables, possibly within a GARCH-MIDAS framework [5, 9, 10].

4. Conclusion

The data in this analysis demonstrates that the US-Iran conflict that erupted at the end of February 2026 would have a significant impact on the oil market. When important straits like the Strait of Hormuz are affected by conflict, the price level of Brent crude oil will fluctuate accordingly, and the market will become more unstable. Early research has shown that geopolitical tensions are closely related to oil price fluctuations, and Brent crude oil is particularly susceptible to these influences. The data reveals two major changes following the outbreak of the conflict. One is that the average monthly price increased by approximately 28%, and the other is that the volatility rate soared from less than 5% before the conflict to over 25%. Statistical tests confirm that both of these changes are real.

However, this study has some limitations. Currently, there is not much data available for this period, which limits the amount of data that can be used, potentially leading to incorrect results or exaggerated impacts. Additionally, the model ignores external factors such as OPEC decisions. If more months of data are added in the future, and some of these additional variables are incorporated into the analysis, the predictions regarding market reactions will become more accurate and credible.

It is also worthwhile to compare this incident with earlier ones. As early as 2025, during the war between Israel and Iran, similar concerns arose regarding disruptions in the Strait of Hormuz. At that time, the price of Brent crude oil rose slightly by about 14%, and then quickly fell back. However, this time, the increase was larger, about 28%, and lasted longer.

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