



Geopolitical Risk and State-Dependent Crude Oil Volatility Forecasting: Evidence from Rolling Out-of-Sample Prediction

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ABSTRACT

This study examines whether geopolitical risk contains incremental predictive information for crude oil market volatility in a rolling out-of-sample forecasting framework. Rather than focusing only on in-sample associations, the analysis evaluates whether the geopolitical risk index improves real-time prediction relative to a benchmark autoregressive model, denoted AR p. The study begins with return forecasting, where the evidence is limited and does not support a stable full-sample predictive role for geopolitical risk. Motivated by this result, the analysis shifts to volatility forecasting and considers two alternative proxies, namely absolute returns and squared returns. These measures capture different aspects of market risk, as absolute returns are more robust to extreme observations, whereas squared returns place greater weight on tail events. The empirical design compares a benchmark ARp model with an augmented ARp+GPR specification under both full-sample and regime-dependent evaluation. High-risk periods are identified from the upper tail of the geopolitical risk distribution. The results show that geopolitical risk does not generate uniform forecasting gains across the full sample. However, its predictive contribution becomes more relevant during high-risk periods, where state-dependent improvements emerge in volatility forecasting, although the strength and form of these gains vary across volatility proxies. Overall, geopolitical risk is better interpreted as a stress-state risk indicator than as a general-purpose predictor of crude oil market movements.

Keywords: Geopolitical Risk; Crude Oil Volatility; Out-Of-Sample Forecasting; State Dependence; Volatility Proxies

JEL Codes : C22; C53; G17; Q43

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1. INTRODUCTION

Crude oil remains one of the most influential commodities in the global economy because its price movements affect production costs, transport systems, inflation expectations, and financial conditions. This central role also means that the oil market is unusually sensitive to geopolitical disturbances. Wars, sanctions, interstate tensions, and terrorist threats affect not only current prices but also expectations about supply conditions, market uncertainty, and the future distribution of risk. In this context, geopolitical risk has become an important information variable for understanding crude oil market behaviour.

Recent research shows that geopolitical conditions are closely connected to oil market fluctuations, especially when the focus shifts from average returns to volatility dynamics. Studies using GARCH-MIDAS, MIDAS-type, and rolling forecast frameworks generally suggest that geopolitical risk can improve oil volatility prediction, particularly when market stress is elevated or nonlinear structures are taken into account (Liu et al., 2019; Mei et al., 2020; Nonejad, 2022; Pan et al., 2023). At the same time, this literature also implies that the predictive role of geopolitical risk is neither simple nor uniform. The fact that a variable is associated with oil market movements does not necessarily mean that it provides incremental forecasting gains once prediction is evaluated in a genuine out-of-sample setting. The relevant issue is therefore not only whether geopolitical risk matters, but whether it improves forecasting performance relative to a parsimonious autoregressive benchmark.

This distinction is particularly important because the choice of forecast target shapes the empirical conclusion. In commodity and financial markets, return predictability is often weak, unstable, and highly sensitive to specification and sample period. By contrast, uncertainty-related indicators are often more informative for volatility than for return direction. In the crude oil literature, this view is consistent with evidence showing that uncertainty measures tend to perform better in volatility forecasting than in mean return forecasting, especially under recursive evaluation and alternative forecast designs (Wei et al., 2017; Liang et al., 2020; Li et al., 2022). This suggests that geopolitical risk may be better interpreted as a driver of market risk amplification than as a stable determinant of future return direction.

A further complication is that the predictive relevance of geopolitical risk is unlikely to be constant over time. Geopolitical shocks are episodic and tend to cluster during periods of heightened tension. As a result, their information content may be limited during relatively tranquil periods but much more pronounced when the market enters a high-risk state. Recent studies increasingly point to time variation, nonlinearity, and regime dependence in the relationship between geopolitical conditions and crude oil markets, whether through regime-switching models, rolling-window analysis, or asymmetric predictive structures (Qian et al., 2022; Li et al., 2023; Wu et al., 2023). A full-sample average forecasting result may therefore conceal the conditions under which geopolitical risk becomes informative.

The measurement of volatility introduces an additional issue. Because volatility is latent, empirical forecasting requires observable proxies. In lower-frequency settings, absolute returns and squared returns are among the most widely used alternatives, yet they do not represent market risk in the same way. Absolute returns are relatively more robust to extreme observations, whereas squared returns place greater weight on tail events. In an oil market

influenced by abrupt geopolitical disruptions, this distinction is economically meaningful rather than purely technical. Comparing these two proxies therefore helps clarify whether the predictive content of geopolitical risk is linked to broad volatility movements or to the tail-sensitive component of market risk. This concern is also consistent with recent forecasting studies showing that oil volatility results depend on model structure, predictor transformation, and the treatment of nonlinearities and extremes (Nonejad, 2022; Huang et al., 2023; Yang et al., 2026).

Against this background, the present study re-examines the predictive relevance of geopolitical risk for crude oil markets within a rolling one-step-ahead out-of-sample forecasting framework. The analysis begins with crude oil returns as the natural baseline target, but it also allows the empirical focus to shift toward volatility forecasting if the evidence indicates that geopolitical risk is more informative about future risk than future direction. To do so, the study compares a benchmark autoregressive model, denoted $AR(p)$, with an augmented $AR(p)+GPR$ specification and evaluates forecast performance using RMSE, MAE, out-of-sample R^2 , and the Clark–West statistic. In addition, the forecasting exercise is implemented for the full sample as well as for high-risk and low-risk periods, which makes it possible to examine whether geopolitical risk functions as a conditional predictor rather than a uniform source of predictive gains.

Although prior studies have established that geopolitical risk is relevant for crude oil market dynamics, three gaps remain. Existing evidence still provides limited direct assessment of whether geopolitical risk improves out-of-sample forecasts relative to a simple autoregressive benchmark. Moreover, the contrast between return forecasting and volatility forecasting has not been sufficiently examined within a unified empirical design. Finally, while recent work increasingly recognises time variation and nonlinear effects, the extent to which the predictive contribution of geopolitical risk is concentrated in high-risk periods and remains robust across alternative volatility proxies is still insufficiently clarified. The present study addresses these issues by integrating target choice, market state, and volatility measurement into the same forecasting framework.

Accordingly, the study is guided by the following research questions:

RQ1. Does geopolitical risk improve the out-of-sample forecasting of crude oil returns and volatility relative to an autoregressive benchmark?

RQ2. Is the predictive contribution of geopolitical risk concentrated in high-risk periods rather than uniformly distributed across the sample?

RQ3. Are the state-dependent forecasting results robust across alternative volatility proxies?

2. DATA AND EMPIRICAL DESIGN

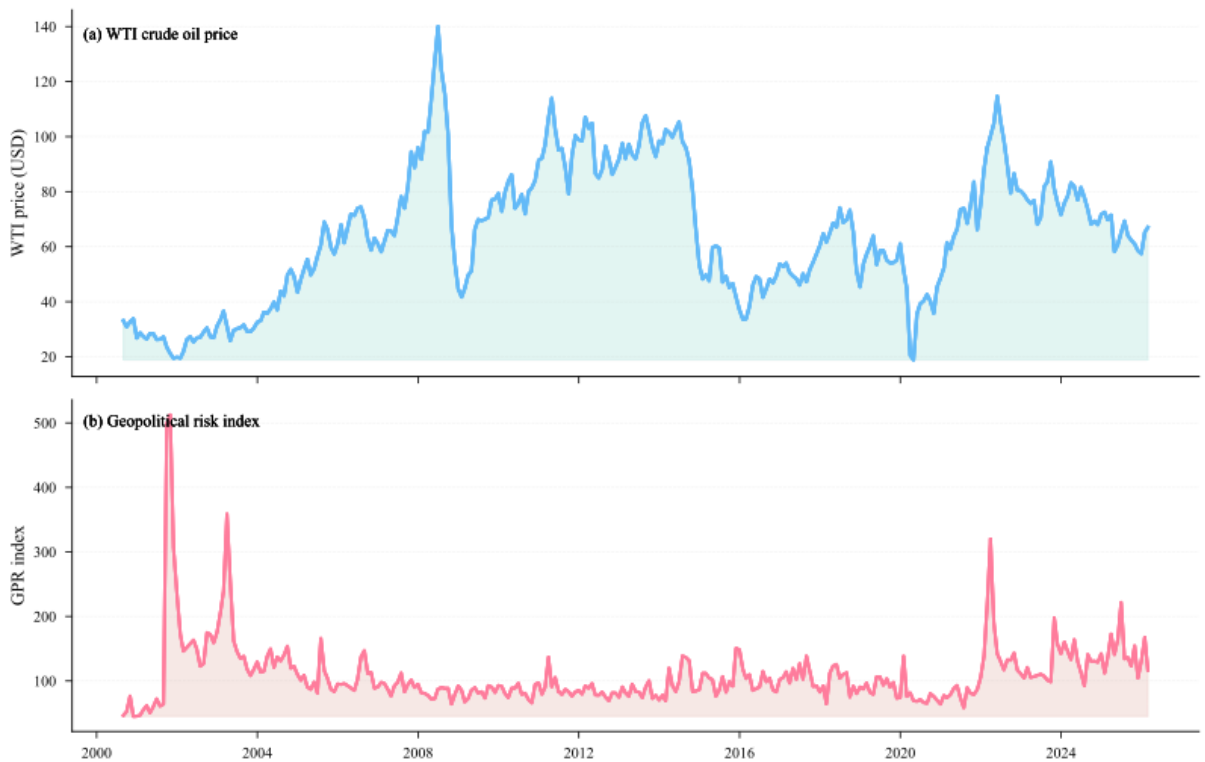
2.1. Data and variable construction

This study uses monthly data on crude oil prices and geopolitical risk. The crude oil series is obtained from Yahoo Finance under the ticker CL=F, which represents WTI crude oil futures prices. Daily observations are converted to monthly frequency by retaining the last available trading-day price in each month, producing a month-end price series stored as

wti_monthly_simple.csv. This frequency choice is suitable because the geopolitical risk indicators are observed monthly and the forecasting exercise is conducted at the monthly horizon, which is also common in recent oil volatility forecasting studies using geopolitical or uncertainty predictors (Mei et al., 2020; Ivanovski & Hailemariam, 2022).

The geopolitical risk data are taken from the official file data_gpr_export.xls, from which the fields month, GPR, and GPRH are extracted. In the empirical analysis, GPR denotes recent geopolitical risk and GPRH denotes historical geopolitical risk. The date variable is aligned to month-end so that the geopolitical risk series can be merged consistently with the WTI month-end price series.

Figure 1. WTI crude oil price and geopolitical risk index



Notes: Panel (a) plots the monthly WTI crude oil price series based on end-of-month observations. Panel (b) plots the monthly geopolitical risk (GPR) index over the same sample period.

Figure 1 plots the monthly WTI crude oil price and the geopolitical risk index. The figure shows that oil prices evolve through persistent swings and reversals, whereas geopolitical risk is characterised by episodic spikes. This contrast supports the treatment of geopolitical risk as an external state variable rather than as a simple correlate of oil price levels.

Let P_t denote the month-end WTI crude oil price in month t . Monthly crude oil returns are defined as log differences,

$$\text{ret}_t = \ln(P_t) - \ln(P_{t-1}) = \ln\left(\frac{P_t}{P_{t-1}}\right).$$

In addition to returns, the analysis considers two volatility proxies. The first is the absolute return,

$$\text{abs}(\text{ret}_t) = |\text{ret}_t|,$$

and the second is the squared return,

$$\text{sq}(\text{ret}_t) = \text{ret}_t^2.$$

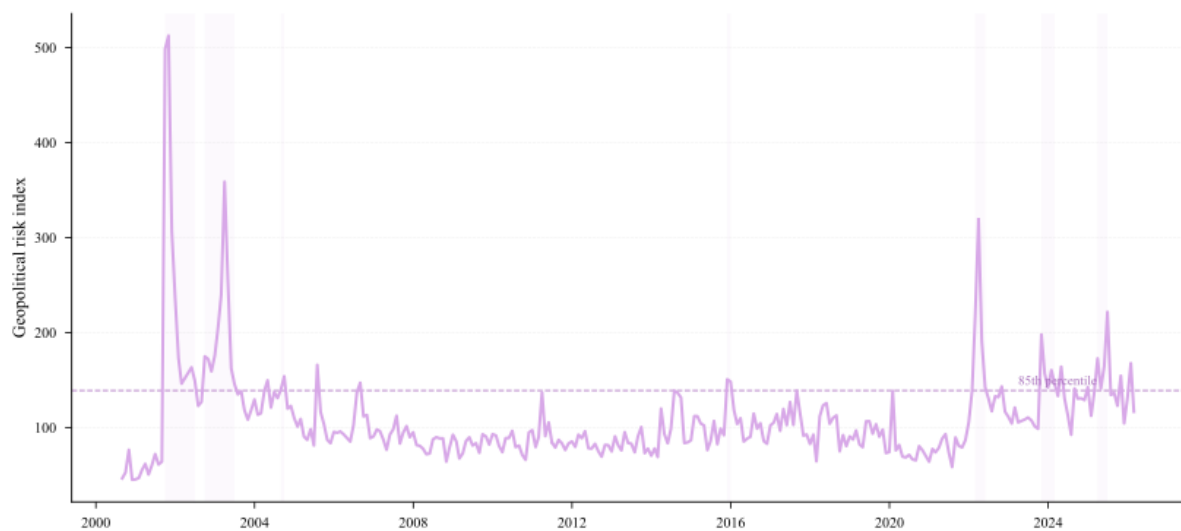
These two measures capture different aspects of market risk. Absolute returns provide a more robust measure of fluctuation magnitude, whereas squared returns assign greater weight to extreme observations. In the present setting, this distinction is substantively relevant because geopolitical shocks may affect both general volatility and tail-sensitive market movements. Recent forecasting studies also suggest that results can vary with volatility measurement and predictor transformation (Nonejad, 2022; Huang et al., 2023).

To examine whether the predictive role of geopolitical risk is state-dependent, the sample is further partitioned into high-risk and low-risk periods. High-risk observations are defined as months in which the GPR index exceeds the 85th percentile of its sample distribution. Formally,

$$\text{HighRisk}_t = \begin{cases} 1, & \text{if } \text{GPR}_t > Q_{0.85}(\text{GPR}), \\ 0, & \text{otherwise} \end{cases}$$

Figure 2 visualises this classification by plotting the GPR series together with the 85th-percentile threshold. High-risk episodes are clustered rather than uniformly distributed across time, which motivates the regime-dependent evaluation reported later in the paper.

Figure 2. High-risk regime identification based on the 85th percentile of GPR



Notes: The figure plots the monthly GPR index and marks the 85th percentile of its sample distribution. Observations above this threshold are classified as high-risk periods in the regime-dependent forecasting analysis.

For reference, Table 1 summarises the variables, forecasting targets, regime definition, and model specifications used in the analysis.

Table 1. Variables, forecasting targets, and empirical design

Component	Definition / specification
Crude oil price	Monthly WTI crude oil price series constructed from end-of-month observations.
Return ret	Monthly crude oil return computed from the oil price series.
Absolute-return volatility proxy abs(ret)	Absolute monthly return, used as the primary proxy for crude oil volatility.
Squared-return volatility proxy sq(ret)	Squared monthly return, used as an alternative volatility proxy for robustness analysis.
Geopolitical risk GPR	Monthly geopolitical risk index used as the predictive risk variable.
Historical geopolitical risk GPRH	Historical geopolitical risk index used as an additional robustness variable in return forecasting.
High-risk regime	Observations for which GPR exceeds the 85th percentile of its sample distribution.
Low-risk regime	Observations below the 85th percentile threshold of GPR.
Benchmark model	AR3specification using three lags of the dependent variable.
Augmented model	AR3+GPR specification including three lags of the dependent variable and lagged GPR.
Historical-risk robustness model	AR3+GPRH specification including three lags of the dependent variable and lagged GPRH.
Forecast design	Rolling-window, one-step-ahead out-of-sample forecasting design.
Forecast evaluation metrics	RMSE, MAE, out-of-sample R^2 , and the Clark–West test.
Regime-dependent evaluation	Forecast performance examined for the full sample and separately for high-risk and low-risk periods.

2.2. Forecasting framework

The empirical objective is to test whether geopolitical risk improves forecast accuracy relative to a parsimonious autoregressive benchmark in a genuine out-of-sample setting. The study therefore adopts a rolling one-step-ahead forecasting design. At each forecast origin, the model is estimated within a rolling window and a one-step-ahead forecast is generated for the target variable. Forecast performance is then evaluated over the resulting out-of-sample sequence. This design is preferable to in-sample comparison because it evaluates predictive usefulness under recursive updating rather than retrospective full-sample fit (Gupta & Pierdzioch, 2022; Liu et al., 2023).

The benchmark specification is an autoregressive model, denoted $AR(p)$,

$$y_t = \alpha + \sum_{i=1}^p \beta_i y_{t-i} + \varepsilon_t,$$

where y_t alternatively denotes ret_t , $abs(ret_t)$, or $sq(ret_t)$, depending on the forecasting target. The augmented model adds lagged recent geopolitical risk,

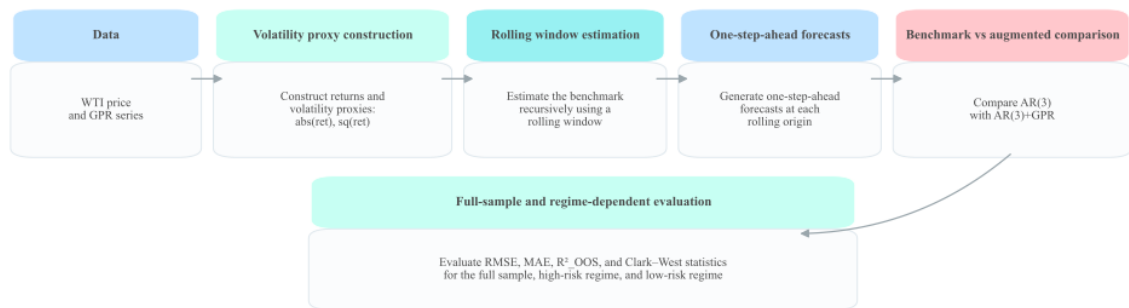
$$y_t = \alpha + \sum_{i=1}^p \beta_i y_{t-i} + \gamma \text{GPR}_{t-1} + \varepsilon_t.$$

For the return-forecasting analysis, a further robustness specification replaces GPR_{t-1} with lagged historical geopolitical risk,

$$y_t = \alpha + \sum_{i=1}^p \beta_i y_{t-i} + \delta \text{GPRH}_{t-1} + \varepsilon_t.$$

Figure 3 summarises the empirical workflow. Starting from the WTI price series and the geopolitical risk data, the analysis constructs returns and volatility proxies, estimates the benchmark and augmented models within a rolling window, generates one-step-ahead forecasts, and then compares predictive performance under both full-sample and regime-dependent evaluation.

Figure 3. Forecasting design schematic



Forecast accuracy is evaluated using RMSE, MAE, out-of-sample R^2 , and the Clark-West statistic. RMSE and MAE measure forecast error based on squared and absolute deviations. The out-of-sample R^2 is defined as

$$R_{\text{OOS}}^2 = 1 - \frac{\sum_t e_{1,t}^2}{\sum_t e_{0,t}^2},$$

where $e_{1,t}$ and $e_{0,t}$ denote the forecast errors of the augmented and benchmark models, respectively. Positive values indicate an improvement relative to the benchmark, whereas negative values indicate deterioration. Since the augmented specification nests the benchmark, the Clark-West statistic is used to assess whether the larger model contains incremental predictive information beyond the autoregressive benchmark (Clark & West, 2007).

The forecasting framework is implemented not only for the full sample but also separately for high-risk and low-risk periods. This design is essential because the paper does not assume that geopolitical risk functions as a uniform predictor across all market conditions. Instead, it evaluates the more plausible proposition that geopolitical information becomes more useful when geopolitical conditions are already elevated. At the same time, the framework permits direct comparison across return forecasting and volatility forecasting, as well as across the two volatility proxies introduced later in the paper. This design is also consistent with recent studies that emphasise rolling-window evaluation, regime sensitivity, and the forecasting relevance of

geopolitical or tail-risk information in crude oil markets (Liu et al., 2023; Xiao et al., 2025; Yang et al., 2026). The next section therefore begins with crude oil return forecasting and then examines whether the predictive role of geopolitical risk becomes more visible once attention shifts from return direction to return volatility.

3. RETURN FORECASTING RESULTS

This section begins with crude oil return forecasting because return prediction remains the most direct starting point in the oil forecasting literature. At the same time, the predictive content of broad geopolitical indicators for crude oil returns is unlikely to be stable. In oil markets, return dynamics are shaped by several offsetting channels, including supply expectations, demand conditions, financial sentiment, storage incentives, and broader macroeconomic uncertainty. As a result, even when geopolitical conditions matter for the market environment, their contribution to return direction may remain weak, asymmetric, or horizon-dependent rather than stable across the sample. This interpretation is consistent with evidence showing that the predictive role of geopolitical information for oil returns varies with forecast horizon, risk decomposition, and short-run structural changes rather than appearing as a uniform full-sample effect (Plakandaras et al., 2019; Zhang et al., 2022; Li et al., 2023).

Table 2. Full-sample out-of-sample forecasting results across targets

Target variable	Model	RMSE	MAE	R^2_{Oos} vs. AR3	Clark–West statistic	p-value
Return ret	AR3	0.1230	0.0814	—	—	—
Return ret	AR3+GPR	0.1239	0.0817	-0.0150	-1.666	0.952
Return ret	AR3+GPRH	0.1202	0.0802	-0.0137	-1.580	0.943
Absolute return abs(ret)	AR3	0.0888	0.0506	—	—	—
Absolute return abs(ret)	AR3+GPR	0.0889	0.0499	-0.0019	1.183	0.119
Squared return sq(ret)	AR3	0.0560	0.0159	—	—	—
Squared return sq(ret)	AR3+GPR	0.0565	0.0156	-0.0200	-0.536	0.704

Table 2 reports the full-sample out-of-sample forecasting results for crude oil returns. Relative to the autoregressive benchmark, the $\text{AR}(p) + \text{GPR}$ specification does not improve return forecasts. The out-of-sample R^2 is negative, which indicates that adding recent geopolitical risk does not reduce mean squared forecast error over the evaluation period. The Clark–West statistic likewise fails to support the claim that the augmented model contains stable incremental predictive information beyond the benchmark. A similar conclusion emerges when recent geopolitical risk is replaced by historical geopolitical risk. Although the $\text{AR}(p) + \text{GPRH}$ specification yields slightly different forecast errors, its performance still does not dominate the benchmark in a robust way. Taken together, these results indicate that geopolitical risk does not generate a stable full-sample forecasting gain for crude oil returns.

This result is economically plausible. Geopolitical variables may alter the level of uncertainty surrounding crude oil markets without translating into a consistent signal for the sign of future returns. Heightened geopolitical tension can raise supply concerns and support prices, but it can also weaken growth expectations, tighten financial conditions, and intensify cross-market spillovers. The resulting return response is therefore ambiguous at the monthly horizon. Recent studies suggest that geopolitical oil price risk operates primarily through downside uncertainty, disaster-type exposure, and broader macro-financial fluctuations rather than through a simple directional return channel (Kilian et al., 2024). Related evidence from higher-order spillover analysis likewise shows that crude oil reacts to economic and geopolitical shocks through changing dependence structures rather than through a single stable mean effect (Cui et al., 2025). Similar conclusions emerge from recent work showing that oil-market responses to geopolitical conditions are often asymmetric and time-varying, which further weakens the case for a uniform return-forecasting effect (He & Sun, 2024; Adeosun et al., 2023).

The limited predictive contribution observed in Table 2 therefore plays an important interpretive role in the paper. It suggests that geopolitical risk should not be treated as a general-purpose return predictor. Instead, its empirical relevance is more likely to lie in the risk dimension of the crude oil market. This interpretation is also supported by the structure of the data presented earlier. The geopolitical risk series is characterised by clustered spikes rather than smooth persistent variation, while the oil price series reflects broader cyclical adjustment. Such a combination naturally points to a predictor that is more closely aligned with changing market stress than with average monthly return direction.

The return results also fit a wider view of commodity-market predictability. Recent work suggests that market efficiency and forecastability in crude oil and related commodity markets are themselves time-varying rather than constant (Kim et al., 2025). Under such conditions, the predictive effect of any single external indicator is unlikely to remain stable over time. This helps explain why a broad geopolitical index may fail to produce a robust full-sample gain in return forecasting even when geopolitical conditions clearly matter for market behaviour. In addition, recent studies on uncertainty transmission and commodity-market interactions indicate that geopolitical and macro-financial shocks are more readily reflected in volatility, spillovers, and higher-order dependence than in the conditional mean of returns (Adeosun et al., 2023; Wu et al., 2023; Selmi et al., 2020; Özdemir et al., 2025).

Accordingly, the evidence from return forecasting should be read as a transition rather than as the endpoint of the empirical analysis. The negative out-of-sample (R^2) values and the lack of Clark–West significance show that geopolitical risk does not provide a stable improvement in forecasting crude oil return direction over the full sample. However, this finding also sharpens the logic of the paper. If geopolitical risk is not a reliable predictor of returns, then its predictive contribution may become more visible once the target variable is redefined in terms of return variability rather than return direction. The next chapter therefore turns to volatility forecasting and examines whether the empirical role of geopolitical risk becomes clearer when attention shifts from crude oil returns to crude oil volatility.

4. VOLATILITY FORECASTING RESULTS

The limited evidence from return forecasting naturally shifts the empirical focus to volatility forecasting. This transition is not ad hoc. Rather, it follows from the economic role of geopolitical risk in crude oil markets. Geopolitical shocks are more likely to alter the scale, persistence, and tail sensitivity of market fluctuations than to generate a stable signal for return direction. Recent studies increasingly treat geopolitical information as a source of volatility, spillover, and tail-risk prediction in energy markets, especially when forecast performance is evaluated out of sample and under stressed conditions. This broader perspective is evident in recent work on crude oil volatility forecasting with geopolitical information, world uncertainty measures, time-varying network spillovers, and tail-risk prediction, all of which point to a closer connection between geopolitical conditions and the risk dimension of oil markets than between geopolitical conditions and the average direction of returns (Delis et al., 2025; Yao & Liu, 2023; Wang & Dong, 2024; Chowdhury et al., 2025; Basdekis et al., 2026).

To formalise the regime-specific comparison, let $e_{0,t}$ denote the forecast error from the autoregressive benchmark and $e_{1,t}$ denote the forecast error from the model augmented with geopolitical risk. The regime-specific out-of-sample fit is measured as

$$R_{OOS,h}^2 = 1 - \frac{\sum_{t \in h} e_{1,t}^2}{\sum_{t \in h} e_{0,t}^2},$$

where h denotes either the high-risk or the low-risk regime. Positive values indicate that the augmented model outperforms the benchmark within a given regime. In addition, the cumulative forecast gain plotted in the figures can be written as

$$CG_h(T) = \sum_{t \in h, t \leq T} (e_{0,t}^2 - e_{1,t}^2),$$

so that an upward-sloping path indicates periods in which the inclusion of geopolitical risk improves forecast performance relative to the benchmark. These two quantities are used jointly because the regime-specific R_{OOS}^2 summarises relative fit, whereas the cumulative gain reveals whether any advantage is persistent or merely driven by a small number of isolated episodes.

Figure 4 provides the descriptive starting point for the volatility analysis by plotting the two volatility proxies used in the paper. Panel (a) reports the absolute-return series, while Panel (b) reports the squared-return series. Both exhibit pronounced volatility clustering, although the squared-return measure displays sharper spikes, reflecting its stronger sensitivity to extreme market movements. This difference is economically meaningful because recent studies show that geopolitical and broader uncertainty conditions can shape not only crude oil volatility itself but also the way volatility propagates across markets and forecasting environments. Evidence from world uncertainty forecasting, time-varying network analysis, country-specific volatility transmission, and market-fear spillovers all suggests that the transmission of geopolitical information becomes more visible once the focus shifts from average returns to the volatility structure of the market (Yao & Liu, 2023; Wang & Dong, 2024; Liu et al., 2023; Xiao et al., 2025).

Figure 4. Volatility proxies over time: absolute and squared returns

Notes: Panel (a) shows the absolute-return volatility proxy, $\text{abs}(\text{ret})$, and Panel (b) shows the squared-return volatility proxy, $\text{sq}(\text{ret})$. These two proxies are used as alternative forecasting targets in the volatility analysis.

4.1. Forecasting absolute-return volatility

The first volatility specification uses absolute returns as the forecasting target. This proxy captures the magnitude of market fluctuations while remaining relatively robust to isolated extremes. It therefore provides a natural first test of whether geopolitical risk improves prediction of broad volatility dynamics rather than only the most extreme outliers. This is useful because several recent studies suggest that the forecasting contribution of geopolitical information may first appear through general volatility measures before becoming visible in more tail-sensitive environments, particularly when the benchmark is parsimonious and the evaluation is conducted in rolling out-of-sample form (Delis et al., 2025; Yang et al., 2026; Huang et al., 2023).

Table 2 shows that, in the full sample, the $\text{AR}(p)+\text{GPR}$ model does not produce a uniform improvement over the autoregressive benchmark when the target variable is $\text{abs}(\text{ret}_t)$. The out-of-sample R^2 is slightly negative, which implies that the inclusion of geopolitical risk does not reduce mean squared forecast error over the entire evaluation period. Although the MAE of the augmented model is marginally smaller, the full-sample evidence remains insufficient to claim a stable and unconditional volatility-forecasting gain.

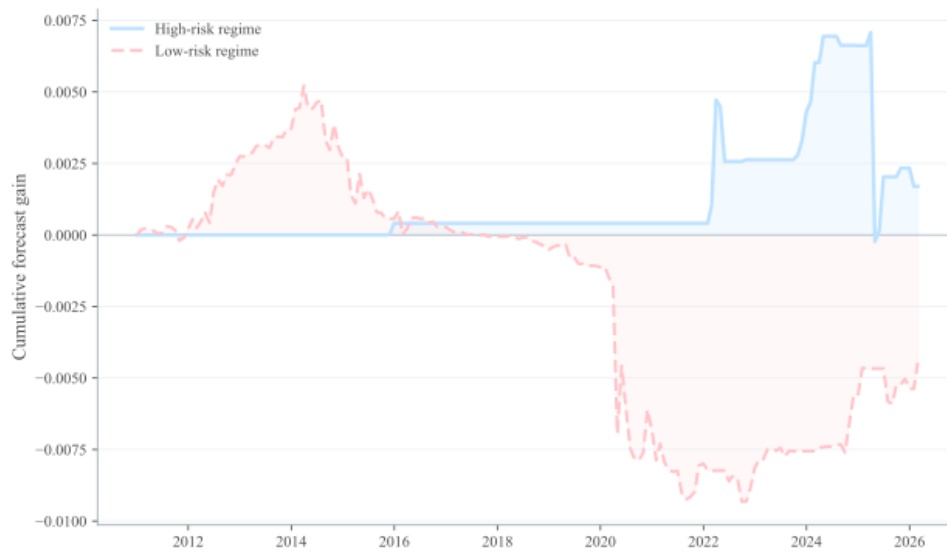
The regime-dependent results are more informative. Table 3, Panel A, shows that once the sample is split by geopolitical state, the predictive role of geopolitical risk becomes more concentrated. In the high-risk regime, the augmented model yields a positive out-of-sample R^2 , indicating that geopolitical risk improves the prediction of absolute-return volatility relative to the benchmark. In the low-risk regime, by contrast, the corresponding R^2_{OOS} is slightly negative and the Clark–West statistic is weak. The evidence therefore points to a conditional forecasting

contribution rather than a uniform one. Geopolitical risk does not systematically improve volatility prediction in normal periods, but it becomes informative when geopolitical conditions move into the upper tail of the risk distribution.

Table 3. Regime-dependent out-of-sample forecasting performance across volatility proxies

Panel A. Absolute-return volatility proxy						
Regime	Model	RMSE	MAE	$R^2_{\text{Oos vs. AR3}}$	Clark–West statistic	p-value
High-risk	AR3	0.0507	0.0416	—	—	—
High-risk	AR3+GPR	0.0498	0.0358	0.0316	1.279	0.108
Low-risk	AR3	0.0926	0.0517	—	—	—
Low-risk	AR3+GPR	0.0927	0.0518	-0.0032	0.248	0.402
Panel B. Squared-return volatility proxy						
Regime	Model	RMSE	MAE	$R^2_{\text{Oos vs. AR3}}$	Clark–West statistic	p-value
High-risk	AR3	0.0123	0.0102	—	—	—
High-risk	AR3+GPR	0.0140	0.0089	-0.2934	1.873	0.038
Low-risk	AR3	0.0593	0.0166	—	—	—
Low-risk	AR3+GPR	0.0599	0.0164	-0.0185	-0.829	0.796

Figure 5 reinforces this interpretation by plotting the cumulative forecast gain for the absolute-return specification across the two regimes. The high-risk path displays a more favourable cumulative pattern, whereas the low-risk path shows little sustained advantage from including geopolitical risk. This visual result matters because it indicates that the high-risk improvement is not generated by a single exceptional month. Instead, the gain accumulates across stressed periods, which is exactly what one would expect if geopolitical information becomes operational when oil markets are already exposed to elevated geopolitical pressure. This reading is consistent with recent findings that volatility spillovers and geopolitical transmission intensify during stress episodes, and that rolling-window forecast gains often become visible only once the evaluation is conditioned on specific market states rather than averaged across the whole sample (Wang & Dong, 2024; Delis et al., 2025; Yang et al., 2026).

Figure 5. Cumulative forecast gain by regime for absolute-return volatility

Taken together, the results for $\text{abs}(\text{ret}_t)$ suggest that geopolitical risk does not improve crude oil volatility forecasting in a full-sample average sense. However, once attention is restricted to high-risk periods, its predictive contribution becomes economically meaningful. The result is therefore consistent with a state-dependent interpretation of geopolitical risk. It acts less like a constant predictor and more like a conditional volatility signal whose usefulness rises when geopolitical stress is already elevated.

4.2. Forecasting squared-return volatility

The second volatility specification uses squared returns as the target variable. Compared with absolute returns, this proxy gives greater weight to extreme observations and is therefore more sensitive to tail-type movements. This feature is especially relevant in the present context because geopolitical shocks often manifest through abrupt and unusually large changes in crude oil prices. Recent studies on energy-market tail risk and extreme volatility similarly suggest that stress-period predictive dynamics can differ materially from those observed in broader volatility measures. This is evident in recent work on geopolitical tail-risk forecasting, black-swan volatility episodes, and deep-learning volatility prediction with geopolitical inputs, all of which indicate that extreme oil-market outcomes may react differently from smoother volatility proxies (Chowdhury et al., 2025; Ren et al., 2026; Li et al., 2026; Basdekis et al., 2026).

As in the absolute-return specification, the full-sample evidence does not support a uniform predictive gain from geopolitical risk. Table 2 shows that when $\text{sq}(\text{ret}_t)$ is used as the target variable, the augmented model produces a negative out-of-sample R^2 , and the full-sample Clark–West statistic is not supportive. Hence, the addition of geopolitical risk does not improve mean squared forecast performance over the full sample.

The regime-specific results again reveal a more nuanced pattern. Table 3, Panel B, shows that in the high-risk regime the out-of-sample R^2 remains negative, which means that the benchmark is still difficult to dominate in mean squared error terms when the target variable heavily weights extreme realisations. However, the Clark–West statistic becomes materially stronger in this regime, indicating that the augmented model contains incremental predictive information relative to the nested autoregressive benchmark. In the low-risk regime, by

contrast, neither the out-of-sample R^2 nor the Clark–West statistic indicates predictive improvement.

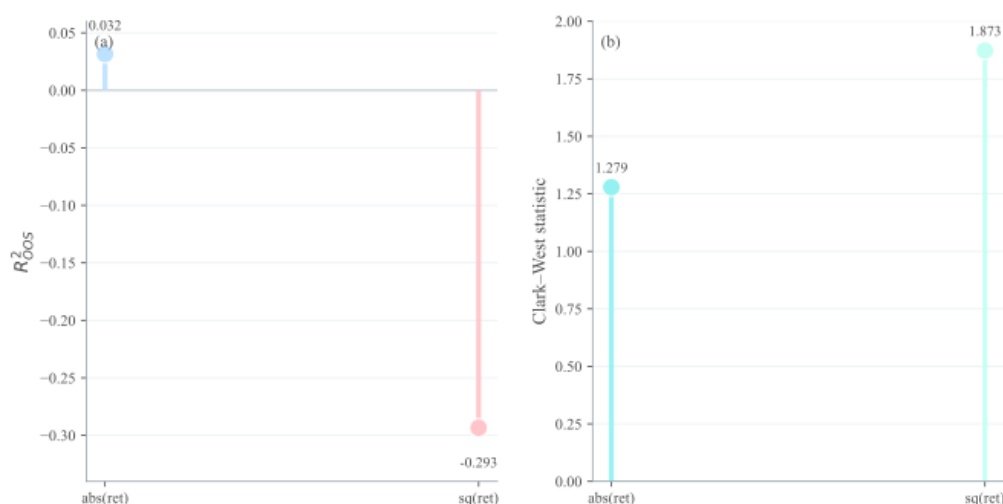
This result should not be read as contradictory. Instead, it suggests that when volatility is represented by a tail-sensitive proxy, geopolitical risk still carries information, but its contribution is more difficult to convert into a broad reduction in mean squared forecast error. Put differently, squared returns impose a stricter forecasting environment because a few extreme realisations can dominate forecast-loss comparisons. Under such conditions, the stronger Clark–West result in the high-risk regime indicates that geopolitical risk is not irrelevant. Rather, it is linked to the more extreme component of crude oil market risk, even if the improvement does not appear as a positive regime-specific R^2_{OOS} . This interpretation is consistent with recent studies that connect geopolitical risk to energy-market tail forecasting, extreme-volatility modelling, and nonlinear predictive systems rather than to uniform average forecasting gains (Chowdhury et al., 2025; Basdekis et al., 2026; Ren et al., 2026; Li et al., 2026).

Figure S1 supports this interpretation by plotting the cumulative forecast gain by regime when squared returns are used as the target. The low-risk regime shows no systematic advantage from including geopolitical risk. The high-risk path, however, evolves differently and indicates that the relative performance of the augmented model is shaped by stressed periods rather than by normal times. Once again, the empirical message is conditional rather than universal.

The squared-return results therefore complement, rather than contradict, the evidence from absolute returns. They suggest that geopolitical risk is tied to the tail-sensitive dimension of crude oil volatility, but that this contribution is more difficult to capture through a single metric. This is precisely why the comparison across volatility proxies is central to the interpretation of the paper.

4.3. Comparative interpretation across volatility proxies

Figure 6. High-risk forecasting comparison across volatility proxies



A comparison across the two volatility proxies clarifies the broader contribution of the paper. Figure 6 summarises the high-risk evidence by reporting, in Panel (a), the regime-

specific out-of-sample R^2 values and, in Panel (b), the corresponding Clark–West statistics for the absolute-return and squared-return specifications. The figure makes clear that the predictive role of geopolitical risk does not take exactly the same form across the two proxies. For absolute returns, the high-risk evidence is expressed more directly through a positive out-of-sample R^2 , which indicates improved mean squared forecast performance. For squared returns, by contrast, the high-risk evidence is more visible through the Clark–West statistic than through the R^2_{OOS} metric.

This divergence is not only statistical but also economic. Since absolute returns provide a smoother representation of fluctuation magnitude, the positive high-risk R^2 suggests that geopolitical risk improves forecasting of broad oil-market volatility under stress. Since squared returns place greater emphasis on extreme realisations, the stronger Clark–West result suggests that geopolitical risk also contains information about the tail-sensitive component of crude oil risk, even when this information does not translate into a simple reduction in mean squared forecast error. The two proxies therefore reveal complementary dimensions of the same mechanism. One captures improvement in general volatility forecasting, whereas the other captures incremental predictive content linked more closely to extreme market movements.

This comparison strengthens the overall interpretation of the paper. First, it confirms that the predictive relevance of geopolitical risk is state-dependent. Across both proxies, low-risk periods provide little support for improvement, whereas high-risk periods are the only setting in which geopolitical information becomes empirically meaningful. Second, it shows that the form of this predictive contribution depends on how volatility is measured. This conclusion aligns with recent studies that emphasise rolling-window evaluation, regime sensitivity, volatility-representation effects, and the forecasting relevance of geopolitical information under stressed market conditions (Yao & Liu, 2023; Chowdhury et al., 2025; Delis et al., 2025; Yang et al., 2026).

Taken together, the volatility-forecasting results establish the main empirical contribution of the paper. Geopolitical risk does not uniformly improve crude oil forecasting over the full sample. However, once the focus shifts from return direction to return volatility, and once the evaluation is conditioned on high-risk states, its predictive contribution becomes substantially more visible. The evidence therefore supports a conditional interpretation of geopolitical risk. It is better viewed as a stress-state risk indicator than as a general-purpose predictor of crude oil market movements.

5. DISCUSSION

The volatility-forecasting results refine the broader interpretation of the paper. Rather than supporting a uniform predictive role for geopolitical risk across the full sample, the evidence indicates that its forecasting relevance is conditional on market stress and on how volatility is represented. This helps explain why the return-forecasting results remain weak. In crude oil markets, geopolitical developments affect prices through multiple and often offsetting channels. Supply disruptions may push prices upward, while weaker demand expectations, tighter financial conditions, and broader uncertainty may exert the opposite effect. At the monthly horizon, these competing forces make return direction difficult to predict in a stable way.

By contrast, volatility provides a more suitable setting in which geopolitical information can become forecast-relevant. Once the analysis is conditioned on high-risk periods, the contribution of geopolitical risk becomes more visible across both volatility proxies, although not in exactly the same form. For absolute returns, the gain appears more directly through a positive out-of-sample R^2 , suggesting improved prediction of broad fluctuation magnitude. For squared returns, the evidence is more nuanced, with the stronger Clark–West statistic indicating incremental predictive information linked more closely to extreme market movements. The two proxies therefore do not contradict each other; rather, they reveal different aspects of how geopolitical stress enters crude oil risk dynamics.

These findings also carry a methodological implication. The predictive value of geopolitical information cannot be assessed independently of target construction, regime definition, and evaluation metric. Whether geopolitical risk appears useful depends not only on the predictor itself, but also on the framework through which forecast performance is judged. At the same time, several limitations should be acknowledged. The monthly frequency may smooth short-run transmission mechanisms, the autoregressive benchmark is intentionally parsimonious, and the regime-based analysis reduces the effective sample size in the high-risk subsample. Even so, the overall evidence supports a restrained but meaningful conclusion: geopolitical risk is better understood as a stress-state risk indicator than as a general-purpose predictor of crude oil market movements.

6. CONCLUSION

This study re-examines the predictive relevance of geopolitical risk for crude oil markets within a rolling one-step-ahead out-of-sample forecasting framework. The results show that geopolitical risk does not provide a robust full-sample forecasting gain for crude oil returns relative to an autoregressive benchmark, indicating that it should not be interpreted as a general predictor of monthly price direction. Once the focus shifts to volatility forecasting, however, a different pattern emerges. Although the augmented model does not uniformly outperform the benchmark over the full sample, its predictive contribution becomes more visible in high-risk periods. This pattern is strongest for absolute returns, while the squared-return results remain more nuanced but still point to incremental predictive information under stress.

The paper contributes by evaluating geopolitical risk from a strict out-of-sample forecasting perspective, by distinguishing clearly between return forecasting and volatility forecasting, and by combining regime-dependent evaluation with alternative volatility proxies in a unified design. Taken together, the findings show that the predictive value of geopolitical risk is state-dependent and sensitive to the way volatility is measured. More broadly, geopolitical risk is better interpreted as a stress-state risk indicator than as a universal forecasting variable.

Future research may examine whether the same pattern holds at higher data frequencies, across alternative forecast horizons, or in richer nonlinear forecasting frameworks. It would also be useful to compare the global GPR index with country-specific or event-specific geopolitical measures in order to assess whether the results reflect the general properties of geopolitical stress or the particular construction of the index itself.

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APPENDICES

Figure S1. Cumulative forecast gain by regime for squared-return volatility



Notes: The figure reports the cumulative forecast gain of the augmented AR3+GPR model relative to the AR3 benchmark when $\text{sq}(\text{ret})$ is used as the target variable. Results are shown separately for high-risk and low-risk regimes.