# Dynamic Linkages and Hedging between Traditional Energy and Green Energy Subsectors under Heterogeneous Geopolitical Risk Shocks

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## ABSTRACT

Using daily observations for West Texas Intermediate (WTI) crude oil futures, the solar ETF (TAN), and the wind ETF (FAN) from January 3, 2019 to December 31, 2025, this paper examines how heterogeneous geopolitical risk shocks reshape the linkages between traditional energy and green-energy subsectors and what these changes imply for hedging. The empirical framework combines marginal ARMA-GARCH models, dynamic conditional correlation generalized autoregressive conditional heteroskedasticity (DCC-GARCH) estimation, quantile regression, and hedging measures. The results show clear time variation and strong persistence in the correlation structure. After the escalation of the Russia-Ukraine conflict, the mean dynamic correlations of WTI-TAN and WTI-FAN decline from 0.1477 and 0.1566 to 0.1220 and 0.1081, respectively. Geopolitical Risk Act (GPRA) remains negative across quantiles, whereas Geopolitical Risk Threat (GPRT) is mainly significant in the lower and middle quantiles. In portfolio terms, wind works better as a baseline hedge in normal periods, while solar shows stronger relative hedging effectiveness during the Red Sea crisis. These findings remain broadly unchanged under an alternative distributional specification and after excluding the extreme observations in 2020.

**Keywords:** geopolitical risk; green energy; DCC-GARCH; quantile regression; hedging

## 1. INTRODUCTION

As the energy transition deepens, the linkage between fossil-fuel assets and green-energy assets has become an important issue in energy finance. The question is not only whether oil and clean-energy prices move together, but also whether their relationship changes under geopolitical stress. Earlier studies show that oil prices, technology stocks, and carbon-market conditions affect clean-energy pricing [7], [8], [9], [10]. More recent work brings geopolitics into the same discussion and suggests that the crude oil-clean-energy relationship becomes state dependent when geopolitical risk intensifies [11], [12].

Recent research also shows that the issue cannot be reduced to average comovement. Differences emerge across higher moments, crisis episodes, and broader transition outcomes [13], [14], [15], [16], [17], [18]. Against this background, this paper asks a narrower question: once geopolitical risk is decomposed into threat and action components, do solar and wind display the same linkage pattern with crude oil? To answer this question, the paper studies West Texas Intermediate (WTI), the solar ETF (TAN), and the wind ETF (FAN) within one framework and traces the analysis from dynamic correlations to quantile responses and hedging outcomes.

## 2. LITERATURE REVIEW AND RESEARCH DESIGN

Early studies on the oil-clean-energy nexus mainly relied on VAR, cointegration, or standard connectedness frameworks. The basic pricing link between oil and alternative-energy assets is well established [7], [8]. Later work shows that this relationship is time varying rather than fixed [9], [10]. More recent studies bring geopolitical conditions directly into the analysis and show that these conditions reshape transmission between fossil-fuel and clean-energy markets [11], [12], [16].

Another line of work emphasizes heterogeneity. Some studies discuss renewable-energy deployment or the broader transition process [13], [17], [18]. Others focus on higher moments, crisis periods, or hedging outcomes [14], [15]. Taken together, these studies show why the oil-clean-energy linkage should not be treated as a single average relationship. At the same time, less attention has been paid to joint evidence at the subsector level, to the distinction between Geopolitical Risk

Threat (GPRT) and Geopolitical Risk Act (GPRA), and to how these differences carry over to portfolio decisions within one empirical setting. This paper addresses that combination directly. It examines solar and wind ETFs separately rather than treating green energy as a single block; it distinguishes geopolitical threats from realized acts within one empirical framework; and it links dynamic-correlation estimates to quantile evidence and hedging performance, so the portfolio implications of heterogeneous geopolitical shocks can be assessed more directly.

# 3. DATA, VARIABLES, AND METHODS

## 3.1 Data and Variables

The sample period runs from January 3, 2019 to December 31, 2025. West Texas Intermediate (WTI) crude oil futures represent traditional energy, while the solar ETF (TAN) and the wind ETF (FAN) represent green-energy subsectors. The explanatory risk variables include the geopolitical risk (GPR) index and its threat (GPRT) and act (GPRA) components [2]. The CBOE Volatility Index (VIX), the U.S. Dollar Index (USDX), and S&P 500 returns are included as control variables. Because the three assets are traded in different markets, their trading calendars are aligned before daily log returns are constructed as follows:

$$r_{i,t} = \ln\left(\frac{P_{i,t}}{P_{i,t-1}}\right) \tag{1}$$

where $r_{i,t}$ denotes the log return of asset i at time t, and $P_{i,t}$ is the closing price of asset i at time t.

## 3.2 Empirical Strategy

For the marginal distributions, WTI is modeled with an ARMA (1,1)-GJR-GARCH (1,1)-sstd specification, whereas TAN and FAN are modeled with ARMA (0,0)-sGARCH (1,1)-sstd specifications [3],[4]. This step is intended to capture heterogeneity in the mean and volatility dynamics before the standardized residuals are entered into a dynamic conditional correlation (DCC) model [1], thereby reducing the risk that misspecified marginal models distort the correlation estimates. The conditional covariance matrix is written as

$$H_t = D_t R_t D_t \tag{2}$$

where $H_t$ is the conditional covariance matrix, $D_t$ is the diagonal matrix of conditional standard deviations, and Rt is the dynamic conditional correlation matrix.

Based on the estimated covariance structure, the dynamic correlations for WTI-TAN and WTI-FAN are extracted and used in the quantile regressions. Quantile regression [5] makes it possible to compare the marginal effects of GPRT and GPRA across different linkage states. For the hedging analysis, the optimal hedge ratio and hedging effectiveness follow the standard definitions in [6] and are measured by

$$\beta_t = \frac{h_{12,t}}{h_{22,t}} \tag{3}$$

where $h_{12,t}$ is the conditional covariance between WTI and the hedging asset, and $h_{22,t}$ is the conditional variance of the hedging asset.

$$HE = 1 - \frac{\mathrm{Var}(r_{h,t})}{\mathrm{Var}(r_{u,t})} \tag{4}$$

where $r_{h,t}$ and $r_{u,t}$ denote the hedged and unhedged portfolio returns, respectively.

# 4. EMPIRICAL RESULTS

## 4.1 Descriptive Characteristics and Marginal Models

The Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests for all three return series reject the unit-root null at the 1% level, indicating that the modeled series are stationary. In distributional terms, WTI is the most volatile asset, with kurtosis reaching 104.143, far above the corresponding values for TAN and FAN. The ARCH-LM tests are also significant for all three series, which confirms pronounced volatility clustering. A constant-variance linear model is therefore not suitable for these data, and GARCH-type methods are warranted.

Table 1. DESCRIPTIVE STATISTICS AND PRELIMINARY TESTS

| Asset | Mean | SD | Skew | Kurt | ARCH-LM p |
|---|---|---|---|---|---|
| WTI | 0.00012 | 0.03359 | -0.439 | 104.143 | 0.000 |
| TAN | 0.00055 | 0.02666 | -0.201 | 3.335 | 0.000 |
| FAN | 0.00037 | 0.01447 | -0.600 | 9.024 | 0.000 |

The marginal-model estimates are reported in Table 2. In the WTI equation, the AR (1), MA (1), $\alpha 1$, $\beta 1$, and $\gamma 1$ terms are all significant, and $\gamma 1 = 0.0831$ points to clear asymmetry in crude-oil volatility. The persistence values for TAN and FAN reach 0.9847 and 0.9736, both above WTI's 0.9429. This means that renewable-energy assets display lower day-to-day volatility than crude oil, but their volatility persistence remains strong.

Table 2. ARGINAL MODELS AND DCC PARAMETERS

| Item | Spec./Parameter | Persist. | Diagn. / Est. |
|---|---|---|---|
| WTI | ARMA (1,1)-GJR | 0.9429 | LB p=0.0113 |
| TAN | ARMA (0,0)-sG | 0.9847 | LB p=0.7632 |
| FAN | ARMA (0,0)-sG | 0.9736 | LB p=0.9641 |
| DCC | dcca1/dccb1 | - | 0.02009/0.94731 |

### 4.2 Dynamic Correlations and Geopolitical Shocks

The DCC estimates show that dcca1 = 0.02009 is significant at the 5% level and dccb1 = 0.94731 is significant at the 1% level. The correlation structure therefore reacts to new shocks, but its dominant feature is persistence. Fig. 1 plots the two dynamic-correlation series. Both rise sharply around 2020 and then retreat gradually. After the escalation of the Russia-Ukraine conflict in 2022, the center of the correlation distribution moves downward rather than continuing toward broader energy-market comovement.

The mean comparison supports the same reading. The average dynamic correlation of WTI-TAN declines from 0.1477 to 0.1220, while the mean for WTI-FAN declines from 0.1566 to 0.1081. The corresponding t-tests are significant for both pairs. Relative to solar, wind exhibits a larger post-conflict decline in linkage. This suggests that green-energy subsectors do not absorb shocks from the traditional energy market in the same way. One possible interpretation is that realized conflicts affect crude oil and green-energy assets through different pricing channels. Oil prices are more directly exposed to supply disruption and geopolitical risk premia, whereas solar and wind ETFs are also tied to equity-market valuation and transition-related expectations. Under that interpretation, conflict escalation can weaken the linkage rather than push the two markets into uniformly tighter comovement.

Figure 1. Time-varying DCC correlations for WTI-TAN and WTI-FAN, with the Russia-Ukraine conflict and Red Sea crisis marked on the time axis.

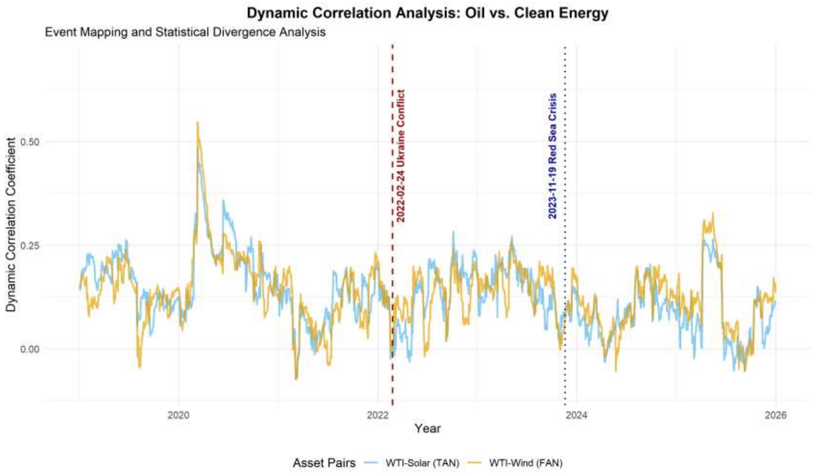


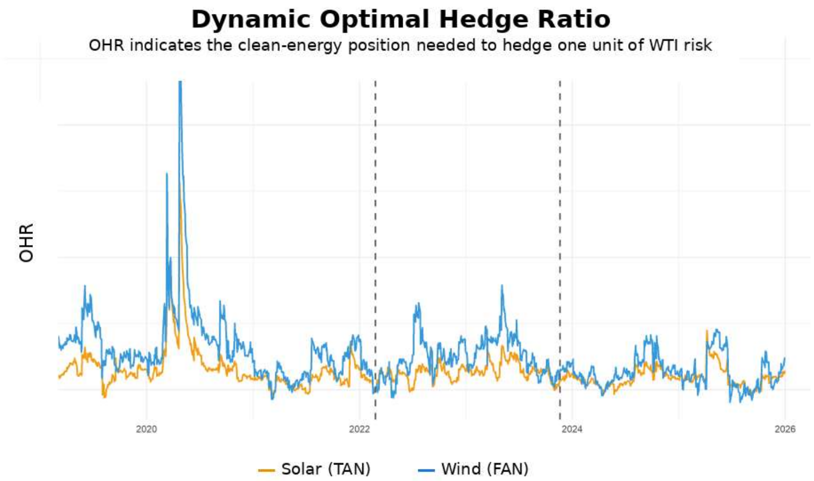

Table 3. RUSSIA-UKRAINE CONFLICT AND CORE QUANTILE-REGRESSION RESULTS

| Pair | Pre | Post | GPRT(τ=.5) | GPRA(τ=.5) |
|---|---|---|---|---|
| WTI-TAN | 0.1477 | 0.1220 | -0.00017*** | -0.00011*** |
| WTI-FAN | 0.1566 | 0.1081 | -0.00018*** | -0.00021*** |

Note: *** indicates significance at the 1% level.

The quantile-regression results are consistent with the mean comparison. For WTI-TAN, GPRT is significantly negative at $\tau = 0.1$ and $\tau = 0.5$ and turns weakly positive at $\tau = 0.9$, whereas GPRA remains negative across all three quantiles. For WTI-FAN, GPRT is significantly negative in the lower and middle quantiles and becomes insignificant in the upper quantile, while GPRA remains negative throughout. These results indicate that the effect of GPRT is more state dependent, whereas the negative effect of GPRA is more stable. Put differently, threat-related information matters more when the oil-clean-energy linkage is low to moderate, while realized conflicts reprice the correlation structure across a wider range of states.

Figure 2. Time-varying optimal hedge ratios for solar and wind positions against WTI risk.



### 4.3 Hedging and Portfolio Implications

Table 4 reports the hedging results across different risk regimes. In the normal period and during the Russia-Ukraine conflict, the mean hedging effectiveness of wind is 0.0319 and 0.0235, slightly above the corresponding values for solar. During the Red Sea crisis, however, the mean hedging effectiveness of solar exceeds that of wind, at 0.0176 versus 0.0118. At the same time, wind has a higher optimal hedge ratio than solar in every regime. This does not automatically imply stronger hedging performance, because the hedge ratio measures the size of the position needed to offset oil risk, whereas hedging effectiveness measures the realized reduction in portfolio variance. In this sample, wind generally requires the larger hedge position, while solar delivers the stronger relative variance reduction in the Red Sea crisis. Fig. 2 plots the time-varying optimal hedge ratios and shows that hedge positions remain dynamic rather than constant over the sample.

Table 4. HEDGING RESULTS ACROSS RISK REGIMES

| Regime | HE-Solar | HE-Wind | OHR-Solar | OHR-Wind |
|---|---|---|---|---|
| Normal period | 0.0300 | 0.0319 | 0.1675 | 0.3397 |
| Russia-Ukraine cf. | 0.0221 | 0.0235 | 0.1349 | 0.2544 |
| Red Sea crisis | 0.0176 | 0.0118 | 0.0918 | 0.1375 |

Taken together with the dynamic portfolio weights, the results suggest that wind remains the main allocation asset throughout the sample, while the portfolio weight of crude oil rises gradually as the risk regime intensifies and solar keeps a relatively small average share. In this sense, wind is closer to the main hedge in normal and medium-risk periods: it carries the larger portfolio weight, requires the larger hedge position, and delivers slightly higher average hedging effectiveness in the first two regimes. Solar plays a different role. Its average weight and hedge ratio stay lower, but its relative hedging effectiveness improves during the Red Sea crisis. The contrast suggests that portfolio weight, hedge ratio, and hedging effectiveness capture different dimensions of risk management and should not be read as interchangeable signals.

## 5. ROBUSTNESS CHECKS

We use two robustness checks to examine whether the main conclusions depend on the distributional assumption or on the extreme observations concentrated in a short period. First, the skewed Student-t distribution in the marginal models is replaced with Generalized Error Distribution (GED). The resulting DCC parameters remain stable, with dcca1 = 0.019277 and dccb1 = 0.949261, which are close to the main estimates. Second, after excluding the extreme observations in the first half of 2020, GPRA remains significantly negative in both sets of quantile regressions. The core findings-that dynamic correlations are highly persistent, that GPRA has the more stable effect, and that wind and solar play different roles in risk management-remain intact.

## 6. CONCLUSION

Using daily data for WTI, TAN, and FAN, this paper examines how heterogeneous geopolitical risk shocks reshape the linkage between traditional and green-energy assets and what this implies for hedging. The evidence shows that the crude oil-green-energy relationship is time varying rather than stable. After major events, the correlation structure changes, but the change is not a uniform increase in comovement.

GPRT shows clearer state dependence, whereas GPRA has a steadier negative association with dynamic correlations. Solar and wind also differ in both linkage sensitivity and hedging function. In the sample, wind is closer to the main hedge in normal and medium-risk periods, while solar becomes relatively more effective during the Red Sea crisis. These differences suggest that green-energy assets should not be treated as a single block in portfolio design. The main conclusions remain stable under the GED alternative specification and after excluding the extreme observations in early 2020. This study remains limited to three representative assets, and future work may extend the analysis to other renewable-energy subsectors and narrower event windows.

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