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Geopolitical Risks and Oil Returns Volatility: A GARCH-MIDAS Approach

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Abstract

In this study, we use the GARCH–MIDAS (Generalized Autoregressive Conditional Heteroskedasticity variant of Mixed Data Sampling) model to explore the relationship between geopolitical risks and oil return volatility. We analyze the daily crude oil returns (West Texas Intermediate (WTI and Brent) and five different monthly measures of geopolitical risks – geopolitical oil price risk (GOPRX), its augmented variant (GOPRX_Augmented), and the conventional geopolitical risks (GPR), geopolitical risks-threats (GPRT), and geopolitical risks-attacks (GPRA). Our results show that higher levels of geopolitical risk are linked to lower oil return volatility, which is due to reduced trading during periods of high geopolitical risks. This finding is consistent across the different GPR indices, with evidence of even out-of-sample predictability. We also discuss the practical implications of our findings for practitioners and policymakers.

Keywords: Geopolitical risks, Oil price volatility, GARCH-MIDAS, Forecast evaluation
JEL Codes: C53, Q41, Q47

1. Introduction

Oil is one of the world's most valuable commodities and has played a significant role in safeguarding national economic and social development and global economic growth. The oil price volatility could impact the economy and inhibit the financial system's stability, which may lead to systemic risks in financial markets. Therefore, oil price volatility has received much attention from policymakers and practitioners in many countries (Truong et al., 2024). Countries like (Nigeria, Venezuela, and some Middle Eastern countries) that depend on oil may experience economic

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distress due to the oil price volatility. Oil price volatility causes major economic instability for oil-producing and exporting countries, particularly those that rely on oil, as they face big losses or gains. These movements create significant uncertainty for independent investors in the oil markets (Salisu and Fasanya, 2013). As a result, both governments and profit-maximizing investors pay close attention to oil price volatility to steer policy and investment decisions

Given the rising tensions in oil-producing nations, which have attendant implications for oil production and supply and, by extension, oil prices, there have been increasing concerns about the role of geopolitics in oil price volatility. Geopolitical risks (GPR) are associated with any conflict or tension between states that impacts global trade, security, and political relations.[1] Furthermore, geopolitical risk differs from other risk indicators and is an important factor in investment decisions (Baur and Smales, 2020; Caldara and Iacoviello, 2022). Conflicts in major oil-producing regions (like the Middle East and Russia) can result in reduced output coming from the affected countries, causing a decrease in global oil supply and, consequently, higher prices.

Theoretically, geopolitical dynamics could influence the supply and demand of oil. The supply policies of OPEC and the United States, for instance, are often motivated by geopolitical factors among countries, leading to elevated levels of oil price uncertainty in the market and, consequently, oil price volatility (Liu et al., 2019). For example, tensions in the Middle East or sanctions on major oil exporters such as Iran or Russia can result in supply shortages, driving higher oil prices (Lee et al., 2021). Countries may be forced by this supply shock to look for more expensive alternatives, which could impact patterns in global trade. However, consumer and business behaviour is impacted by fluctuations in oil prices. Rising transportation and industrial costs may reduce demand due to higher oil prices, which could eventually result in a fall in economic activity. The response of net oil-exporting countries to oil shocks is more substantial and long-lasting than that of net oil-importing countries. While net exporters gain from higher profits but must deal with volatile revenue streams, the dynamics negatively impact net importers through increased trade deficits and inflation.

[1] https://hbr.org/2022/03/research-when-geopolitical-risk-rises-innovation-stalls

Evidence in the literature on the relationship between geopolitical risks and the oil market is mixed. Some studies indicate a positive and pronounced relationship between oil volatility and changes in geopolitical risk during periods of rising geopolitical uncertainty. A positive and strong relationship is highly expected when the countries at war are major suppliers or consumers of oil (Bouoiyour et al., 2019; Li et al., 2020; Lee et al., 2021; Qian et al., 2022; Jiao et al., 2023; Wu et al., 2023, Truong et al., 2024). However, contrary to the previous findings, some other studies have found a negative relationship between oil volatility and geopolitical risk (GPR) due to the decreasing oil demand (Plakandaras et al., 2019; Qin et al., 2020; Zhang et al., 2022).

We contribute to the literature by employing five GPR indices, namely the geopolitical oil price risk (GOPRX), its augmented variant (GOPRX_Augmented) developed in this study [see the data description section for technical details], and the conventional geopolitical risks (GPR), geopolitical risks-threats (GPRT), and geopolitical risks-attacks (GPRA) together with the generalized autoregressive conditional heteroskedasticity (GARCH) variant of the mixed data sampling (MIDAS), i.e., the GARCH-MIDAS model where the GPR index is incorporated as an exogenous [monthly frequency] predictor of daily oil price volatility. This is to show how different aspects of geopolitical risks can influence oil prices. Unlike the previous studies, our choice of the GARCH-MIDAS model is motivated by the mixed frequency nature of the relevant series, where the GPR indexes are consistently available at a monthly frequency while the oil price data is daily. Rather than aggregate the series to a lower frequency, we prefer to preserve the inherent salient features of the series by utilizing the data at their "natural" frequencies which helps to circumvent informal loss or minimize any potential bias due to aggregation. In addition, unlike the previous studies, our analyses are partitioned into the in-sample predictability analysis and the out-of-sample forecast analysis since significant in-sample predictability outcomes do not necessarily translate into improved out-of-sample forecast outcomes. The former permits us to assess the extent of the impact of monthly geopolitical risk variants (GOPRX, GOPRX_ Augmented, GPR, GPRA, and GPRT) on oil price volatility. In the latter case, we assess the out-of-sample forecast precision of the contending geopolitical risks-based GARCH-MIDAS models in comparison with the conventional GARCH-MIDAS (benchmark) model with realized volatility.

In summary, we have found that the five geopolitical risk proxies have relatively equal impacts on oil price volatility. These different types of geopolitical risks show some potential for predicting oil price volatility, with consistently negative predictability coefficients. This means that during high geopolitical risk periods, the volume of oil trade tends to decrease, potentially leading to reduced market volatility. The rest of the paper is organized as follows. Section 2 describes the data and methodology used in the study. Section 3 discusses the empirical result, and section 4 concludes.

2. Data and Methodology

The data utilized in this study consist of daily crude oil prices (West Texas Intermediate (WTI) and Brent) and five different monthly measures of uncertainty – geopolitical oil price risk (GOPRX), its augmented variant (GOPRX_Augmented) developed in this study, and the conventional geopolitical risks GPR), geopolitical risks-threats (GPRT) and geopolitical risks-attacks (GPRA). The data period extends from January 2, 2004, to April 30, 2024, whose period is governed by the available data scope for GOPRX for easy comparison of results across the different GPR indices. The oil prices were obtained from the US Energy Information Administration database: https://www.eia.gov/dnav/pet/pet_pri_spt_s1_d.htm; the searched keywords were sourced from the Google Trends database: https://trends.google.com/trends/explore, and; the geopolitical risks were collected from: https://www.matteoiacoviello.com/gpr.htm.

The geopolitical oil price risk series is drawn from the comprehensive Bonaparte (2019) study: https://business.ucdenver.edu/jpmorgancenter/applied-research/geopolitical-oil-price-risk-index-goprx, which employed a meticulous process of using Google trends search volumes of selected keywords that are associated with oil and politics and sub-listed under four broad categories – sanction (Oil Sanction, Iraq Sanction and Iran Sanction), countries under political stress (Saudi Arabia Oil, Venezuela Oil, Libya Oil, Iraq Oil, Russia Oil, and Syria Oil), political events (Middle Eastern War, Israeli Arab Conflict, Gulf War, Terrorism, Disruption Oil, and OPEC), and economic uncertainty (Oil Price Uncertainty, Oil Uncertainty, Strait of Hormuz Oil, Gulf of Aden Oil and Suez Canal Oil). The search volumes associated with these variables were combined and modified using a factorial analyses econometric method and normalized to lie between 0 and 100. The extreme low and high values are respectively indicative of the minimum and maximum geopolitical risks.

The originally developed GOPRX ended in May 2019; hence, we extend the time period to more recent dates and also augment the list of searched keywords with three additional historical events – the Russia-Ukraine War, the Israel-Hamas War and the Israel-Iran War. This is informed by the need to further accommodate the recent geopolitical issues. Similarly, the augmented variant is normalized as with the original variant. The crude oil variables, which have been transformed into returns, as well as the geopolitical risk variants, are summarized in Table 1. The oil returns were both positive on average. While all five variants of the geopolitical risk are positively skewed, the two oil return series are negatively skewed, and all variables are leptokurtic, exhibiting a kurtosis level greater than 3. All the series except GPRA exhibit evidence of the presence of heteroscedasticity and serial correlation at the specified lags. The inherent features of the daily (high) frequency oil returns suggest the appropriateness of a GARCH model framework while the mixed nature of the variables – predicted and predictor; suggest the incorporation of a MIDAS framework; hence, the GARCH-MIDAS model framework that is adopted for this study.

Table 1: Summary and Preliminary Results

	Mean	Standard Deviation	Skewness	Kurtosis	Observations	$ARCH(1)$	$ARCH(10)$	$Q(1)$	$Q(10)$	$Q^2(1)$	$Q^2(10)$
Monthly Frequency											
$GOPRX$	27.34	17.51	1.46	5.26	244	16.93^{***}	2.05^{**}	0.25	78.59^{***}	16.20^{***}	77.40^{***}
$GOPRX\_Agmtd$	36.00	16.26	1.15	4.76	244	9.10^{***}	0.59	0.23	68.02^{***}	8.94^{***}	34.32^{***}
GPR	99.43	28.39	2.80	18.06	244	35.09^{***}	3.56^{***}	0.3	3.74	31.36^{***}	33.28^{***}
$GPRA$	95.33	37.46	1.44	5.64	244	0.29	0.14	1.07	11.01	0.3	1.42
$GPRT$	103.52	37.43	3.40	23.34	244	130.72^{***}	14.22^{***}	0.33	5.81	86.64^{***}	97.88^{***}
Daily Frequency											
$RWTI$	0.02	2.82	-0.14	42.43	5206	1676.64^{***}	242.47^{***}	4.00E-05	83.49^{***}	672.50^{***}	982.72^{***}
$RBRENT$	0.02	2.64	-2.21	92.87	5206	771.52^{***}	94.78^{***}	2.00E-06	68.02^{***}	1269.40^{***}	3824.00^{***}

Note: The figures in each cell are the estimated MIDAS slope coefficients associated with the incorporated geopolitical risk proxy and their corresponding standard errors in square brackets. The ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels, respectively. GOPRX – geopolitical oil price risk; GOPRX_Augmented – the Augmented geopolitical oil price risk; GPR – geopolitical risk; GPRA – geopolitical risk attack; and GPRT – geopolitical risk threat. RWTI and RBRENT denote returns on global crude oil (WTI and Brent). ARCH- Autoregressive Conditional Heteroscedasticity effect test, which is a formal test for volatility; and the Q and Q^2 – Q-statistic and Q^2 –statistic testing for the presence of autocorrelation and higher order autocorrelation, respectively; at lags 1, 10.

We employ the conventional GARCH-MIDAS model framework to assess the in-sample predictability of daily oil price returns due to monthly geopolitical risk variants ($GOPRX$, $GOPRX\_Agmtd$, GPR, $GPRA$, and $GPRT$). The GARCH-MIDAS model, following Engle et al.

(2013), comprises the constant unconditional mean and the conditional variance that is multiplicatively decomposed into high and low-frequency components. The model specification is defined in Equations (1) - (4) as:

$$r_{i,t} = \mu + \sqrt{h_{i,t} \times \tau_t} \times \varepsilon_{i,t}, \qquad \forall\ i = 1,2,\ldots,N_t \tag{1}$$

$$h_{i,t} = \left(1-\alpha-\beta\right) + \alpha \frac{\left(r_{i-1,t}-\mu\right)^2}{\tau_t} + \beta h_{i-1,t} \tag{2}$$

$$\tau_i^{(rw)} = m_i^{(rw)} + \theta_i^{(rw)} \sum_{k=1}^{K} \phi_k\left(\omega\right) X_{i-k}^{(rw)} \tag{3}$$

$$\phi_k\left(\omega\right) = \frac{\left[1-k/\left(K+1\right)\right]^{\omega-1}}{\sum_{j=1}^{K}\left[1-j/\left(K+1\right)\right]^{\omega-1}} \tag{4}$$

$$\varepsilon_{i,t} \mid \Phi_{i-1,t} \sim N(0,1) \tag{5}$$

where $r_{i,t} = ln\left(P_{i,t}\right) - ln\left(P_{i-1,t}\right)$ denotes the returns on global crude oil (WTI and Brent) prices $\left(P_{i,t}\right)$ on the i^{th} day of the month t,with N_t denoting the number of days in a given month t; μ is the constant unconditional mean of the stock returns; $h_{i,t}$ and τ_t are respectively the short- and long-run components of the conditional variance $\left(\sqrt{h_{i,t} \times \tau_t}\right)$ part of Equation (1), with the former assuming a GARCH(1,1) process; in Equation (2), α and β respectively denote the ARCH and GARCH terms, with some imposed restrictions such that $\alpha > 0$, $\beta \geq 0$ and $\alpha + \beta < 1$; in Equation (3), m represents the long run constant, θ represents the slope coefficient that indicates the predictive potential or otherwise of the geopolitical risks variants for global oil price returns, $\phi_k\left(w\right)$ is a flexible (Colacito et al., 2011) one parameter beta polynomial weighting scheme[2], with the assumptions that $\phi_k\left(w\right) \geq 0,\ k = 1,2,\ldots,K$ and $\sum_{k=1}^{K}\phi_k\left(w\right) = 1$, required for the satisfaction of the model identification condition; the constraint $\left(w > 1\right)$ ensures that larger weights are assigned to more recent than distant lags of the observations, X_{i-k} represents the exogenous predictor (the geopolitical risks variants), and the superscript "*rw*" indicating that a rolling window framework

[2] This is obtained from the two-parameter beta weighting scheme $\phi_k\left(\omega_1,\omega_2\right) = \left[k/\left(K+1\right)\right]^{\omega_1-1} \times \left[1-k/\left(K+1\right)\right]^{\omega_2-1} \Big/ \sum_{j=1}^{K}\left[j/\left(K+1\right)\right]^{\omega_1-1} \times \left[1-j/\left(K+1\right)\right]^{\omega_2-1}$ by constraining ω_1 to 1 and setting $\omega = \omega_2$.

is used in the estimation process; while $\varepsilon_{i,t} \mid \Phi_{i-1,t}$ denotes that the information set which is available at the $(i-1)^{th}$ day of the month t is normally distributed.

For the purpose of robustness, we consider further evaluation of the predictability stance by assessing the out-of-sample forecast precision of the contending geopolitical risks-based GARCH-MIDAS models in comparison with the conventional GARCH-MIDAS-RV (benchmark) model, using the modified Diebold and Mariano (Harvey et al., 1997) test defined in Equation (6). The modified Diebold and Mariano is an extension of the conventional Diebold and Mariano (1995) test defined in Equation (7), that is suited for formal comparison of paired non-nested models. The statistics are defined as follows:

$$DM^* = \left(\sqrt{\frac{T+1-2h+T^{-1}h(h-1)}{T}} \right) DM \tag{6}$$

$$DM = \frac{\bar{d}}{\sqrt{V(d)/T}} \sim N(0,1) \tag{7}$$

where DM^* represents the modified DM statistic; T represents the length of the out-of-sample periods of the forecast errors and h denotes the forecast horizon; $\bar{d} = 1/T\left[\sum_{t=1}^{T} d_t\right]$ represents the average of the loss differential, $d_t \equiv g(\varepsilon_{it}) - g(\varepsilon_{jt})$; $g(\varepsilon_{it})$ and $g(\varepsilon_{jt})$ are respectively the loss functions of the forecast errors, ε_{it} and ε_{jt}, from the contending models; while $V(d_t)$ represents the unconditional variance of the loss differential d_t. The null hypothesis asserts equality in the forecast precision of the contending model pairs $(H_0 : d = 0)$ against a mutually exclusive alternative, $(H_1 : d \neq 0)$. Non-rejection of the null would imply that the forecast precisions of the paired models do not differ markedly, one from the other. The associated sign of the DM* statistic determines the direction of preference, where a negative DM* statistic indicates the outperformance of the contending GARCH-MIDAS predictive model variant over the stated benchmark model, and the converse if the DM* statistic is positive. We employ the full data sample, leaving out the last 120 data points, for the in-sample estimation and the left-out 120 data points for out-of-sample forecast evaluation, with 20-, 60- and 120-day ahead forecast horizons.

3. Empirical Results

Here, we present the in-sample predictability results depicted by the slope coefficient, θ, from the geopolitical risks-based GARCH-MIDAS model estimation, using the full data sample (results are presented in Table 2). The intuition is to ascertain the predictive potential, or otherwise, of the geopolitical risk variants for global crude oil (WTI and Brent) returns. We also stretch the evaluation of the predictability stance beyond the in-sample to assess whether the observed predictability is maintained in the out-of-sample forecast periods (results are presented in Tables 3 – 5 for different benchmark models and for three different forecast horizons). The intuition is to ensure the robustness of the predictive stance across sample forecast periods.

On the in-sample predictability, we find the five variants of geopolitical risks to exhibit some predictive potentials for modelling oil price return volatility, with consistent significantly negative nexuses with the latter. Also, the magnitude of the impacts of the five geopolitical risk proxies on oil return volatility is relatively equal. Imperatively, higher levels of geopolitical risks or global uncertainty impede the gains on oil investments. This stance is observed across all five variants of geopolitical risks, regardless of the crude oil proxy being modelled. This is expectedly so, given that oil production is usually impeded in affected oil-producing economies during heightened geopolitical tensions, due to geopolitical risks reducing global demand following economic contractions (Cunado et al., 2019; Caldara and Iacoviello, 2022). This consequently affects trade volume and volatility and, subsequently, profitability. From another perspective, the period of heightened geopolitical tension is usually characterized by the reallocation of available resources to safe-haven or hedge assets as a way to safeguard investments against loss. Hence, the volume of trade concerning oil tends to reduce for increased investment in alternative, safer assets. The observed negative nexus clearly points to the vulnerability of oil-based assets to geopolitical tension.

For the out-of-sample forecast evaluation, we employ the modified Diebold and Mariano test to assess the forecast precision of the contending predictive models in comparison with the conventional GARCH-MIDAS-RV as a benchmark model. We expect a significantly negative

DM* statistic for our geopolitical risk-based GARCH-MIDAS predictive model to outperform the conventional GARCH-MIDAS-RV model and the converse to imply that the benchmark model performed better. The exercise is conducted for the different geopolitical risk proxies and three different out-of-sample forecast horizons – 20-, 60- and 120- days ahead (see results in Table 3). The reported DM* statistics are all significantly negative, which indicates that our geopolitical risk-based GARCH-MIDAS models consistently outperformed the GARCH-MIDAS-RV model, regardless of the stated forecast horizons. This is an indication that the geopolitical risk proxies, incorporated into our predictive model frameworks, provide tangible information that improves the forecast of oil return volatility beyond the estimation sample period to the out-of-sample periods. Intuitively, the realized volatility of the oil market alone may not be as informative as the incorporated geopolitical risk proxies. Hence, geopolitical risk proxies serve as good predictors for oil volatility modelling.

Table 2: In-Sample Predictability Result (Full Data Sample)

Predictor	$\boldsymbol{Brent}$	$\boldsymbol{WTI}$
$GOPRX$	-0.0184*** [0.0049]	-0.0159*** [0.0059]
$GOPRX\_Augmented$	-0.0184*** [0.0049]	-0.0159*** [0.0059]
GPR	-0.0186*** [0.0049]	-0.0160*** [0.0059]
$GPRT$	-0.0185*** [0.0049]	-0.0161*** [0.0059]
$GPRA$	-0.0149*** [0.005]	-0.0160*** [0.0059]

Note: The figures in each cell are the estimated MIDAS slope coefficients associated with the incorporated geopolitical risk proxy and their corresponding standard errors in square brackets. The *** indicates the statistical significance of the estimates at a 1% significance level. GOPRX – geopolitical oil price risk; GOPRX_Augmented – the Augmented geopolitical oil price risk; GPR – geopolitical risk; GPRA – geopolitical risk attack; and GPRT – geopolitical risk threat.

Table 3: Modified Diebold and Mariano Results (GARCH-MIDAS-RV is Benchmark)

Predictor	$\boldsymbol{h = 20}$	$\boldsymbol{h = 60}$	$\boldsymbol{h = 120}$
	Brent		
$GOPRX$	-3.7420***	-5.8693***	-8.7672***
$GOPRX\_Augmented$	-3.7406***	-5.8692***	-8.7677***
GPR	-3.8073***	-5.9288***	-8.8033***
$GPRT$	-3.7904***	-5.9074***	-8.7885***
$GPRA$	-3.8691***	-5.9995***	-8.8469***
	WTI		

$GOPRX$	-3.0128***	-5.3535***	-9.1433***
$GOPRX\_Augmented$	-3.0015***	-5.3464***	-9.1386***
GPR	-3.1426***	-5.4285***	-9.199***
$GPRT$	-3.1202***	-5.4084***	-9.1809***
$GPRA$	-3.1905***	-5.464***	-9.2308***

Note: The figures in each cell are the modified Diebold and Mariano statistics with *** indicating statistical significance at a 1% level of significance. The significant negative estimates imply that the geopolitical risks-based GARCH-MIDAS model forecast precision is higher than the conventional GARCH-MIDAS-RV model forecast precision, while significant positive estimates denote the outperformance of the latter over the former. GOPRX – geopolitical oil price risk; GOPRX_Augmented – the Augmented geopolitical oil price risk; GPR – geopolitical risk; GPRA – geopolitical risk attack; and GPRT – geopolitical risk threat.

Furthermore, we compare the forecast precision of GARCH-MIDAS models that incorporate the augmented variant of the GOPRX and the conventional GPR variants separately with the GARCH-MIDAS-GOPRX model (the benchmark model in this pair) for oil return volatility (see result in Table 4). We find that the augmented variant underperformed the original variants across the forecast horizons. This is indicative that the information provided by the augmented GOPRX series is not sufficient to improve the precision achieved by GARCH-MIDAS-GOPRX further. However, the GPR, GPRA and GPRT-based models are all found to be more accurate than the GARCH-MIDAS-GOPRX model in the forecast of oil return volatility. This is unsurprising given that GPR, GPRA and GPRT are a broader spectrum of geopolitical uncertainty measures, depicting uncertainty that is not just oil-related as with the GOPRX variants. This feat is sustained even when the GPR, GPRA and GPRT-based GARCH-MIDAS models were compared with the GOPRX_Augmented (see the result in Table 5).

Table 4: Modified Diebold and Mariano Results (GARCH-MIDAS-GOPRX is the benchmark)

Predictor	$h = 20$	$h = 60$	$h = 120$
	Brent		
$GOPRX\_Augmented$	4.6227***	0.9121	-0.6773
GPR	-5.2233***	-6.0650***	-6.4266***
$GPRT$	-4.9474***	-5.2507***	-5.9030***
$GPRA$	-5.3543***	-6.699***	-6.6782***
	WTI		
$GOPRX\_Augmented$	5.4291***	4.6734***	3.9403***
GPR	-5.2586***	-4.9328***	-4.3622***
$GPRT$	-4.7610***	-3.3791***	-3.0711***
$GPRA$	-5.4289***	-5.9338***	-4.5645***

Note: The figures in each cell are the modified Diebold and Mariano statistics with *** indicating statistical significance at a 1% level of significance. The significant negative estimates imply that the row-named geopolitical risks-based GARCH-MIDAS model forecast precision is higher than the conventional GARCH-MIDAS-GOPRX model forecast precision, while significant positive estimates denote the outperformance of the latter over the former. GOPRX – geopolitical oil price risk; GOPRX_Augmented – the Augmented geopolitical oil price risk; GPR – geopolitical risk; GPRA – geopolitical risk attack; and GPRT – geopolitical risk threat.

Table 5: Modified Diebold and Mariano Results (GARCH-MIDAS-GOPRX_Augmented is benchmark)

Predictor	$h = 20$	$h = 60$	$h = 120$
Brent			
GPR	-5.2156***	-5.9482***	-6.2678***
$GPRT$	-4.9415***	-5.1234***	-5.7101***
$GPRA$	-5.3511***	-6.6372***	-6.6005***
WTI			
GPR	-5.2741***	-4.9192***	-4.3393***
$GPRT$	-4.8396***	-3.5193***	-3.1757***
$GPRA$	-5.4292***	-5.8668***	-4.5458***

Note: The figures in each cell are the modified Diebold and Mariano statistics with *** indicating statistical significance at 1% level of significance. The significant negative estimates imply that the row-named geopolitical risks-based GARCH-MIDAS model forecast precision is higher than the conventional GARCH-MIDAS-GOPRX_Augmented model forecast precision, while significant positive estimates denote the outperformance of the latter over the former. GOPRX_Augmented – the Augmented geopolitical oil price risk; GPR – geopolitical risk; GPRA – geopolitical risk attack; and GPRT – geopolitical risk threat.

4. Conclusion

In this paper, we examine the relationship between geopolitical risk and oil price volatility using the daily crude oil prices (WTI and Brent) and five different monthly measures of uncertainty – geopolitical oil price risk (GOPRX), its augmented variant (GOPRX_Augmented) developed in this study, and the conventional geopolitical risks GPR), geopolitical risks threat (GPRT) and geopolitical risks Attacks (GPRA). The data period extends from January 2, 2004, to April 30, 2024. We adopt the generalized autoregressive conditional heteroskedasticity (GARCH) variant of the mixed data sampling (MIDAS), i.e., the GARCH–MIDAS technique as originally developed by Engle et al. (2013), which enables the integration of variables collected at various data frequencies into a single predictability model framework. We evaluate both the in-sample and the out-sample predictability of the various GPR indices for oil return volatility.

The results indicate that the five distinct geopolitical risk variations can anticipate oil price returns to some extent, and their correlations with the latter are consistently quite negative. Furthermore, in terms of magnitude, the five geopolitical risk proxies have nearly the same impact on oil price volatility. Consequently, higher levels of geopolitical risk limit the returns from oil investments, and with reduced oil trading, volatility declines. The out-of-sample forecast evaluation shows the superiority of the GPR-based GARCH-MIDAS models over the benchmark model without the GPR data. The study suggests that individuals involved in the oil futures market, such as policymakers and investors, should carefully monitor significant geopolitical events. This may enhance the accuracy of predictions regarding oil volatility and prompt discussions on alternative oil sources, given the increasing uncertainties in the crude oil market resulting from recurring geopolitical tensions in certain oil-producing countries.

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