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The impact of geopolitical risk on energy and precious metal commodity markets using the DCC-GARCH MIDAS model

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Abstract

Purpose – This study aims to investigate the impact of geopolitical risk on selected energy and precious metal commodities, namely WTI crude oil, Brent crude oil, natural gas, gold and silver.

Design/methodology/approach – The study uses a Dynamic Conditional Correlation Generalized Autoregressive Conditional Heteroscedasticity Mixed Data Sampling (DCC GARCH MIDAS) model to examine the relationship between geopolitical tensions and commodity price volatility. This framework enables the integration of lower-frequency geopolitical risk measures with higher-frequency commodity price data, providing a nuanced view of their dynamic linkages.

Findings – The results confirm that energy commodities, particularly the two benchmark crude oils (WTI and Brent), are highly sensitive to geopolitical uncertainty. The strongest positive correlation between geopolitical risk and oil prices is observed during the Russia–Ukraine invasion. In contrast, gold and silver exhibit relatively low correlations with geopolitical risk and their price responses appear to be more event-specific.

Originality/value – This study contributes to the literature on geopolitical risk by jointly examining its effects on both energy commodities and precious metals. The findings show that gold's hedging capacity is not consistently effective, as its role as a hedge appears to depend on the nature of the geopolitical event. Overall, the results provide useful insights for risk management in periods of heightened geopolitical uncertainty.

Keywords Geopolitical risks, Commodity prices, DCC GARCH MIDAS

Paper type Research paper

1. Introduction

Commodities like crude oil, natural gas, gold and silver are important financial assets that provide a source of economic activities all over the world. The price volatility of commodities presents huge challenges to investors, policymakers and financial analysts. Market volatility could be exacerbated by events like trade wars, the conflict between Russia and Ukraine, the current energy crisis in Europe and even the situation in the Middle East

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(Liu *et al.*, 2024). Geopolitical risk, macroeconomic uncertainty and commodities are interacting in a more complicated way because the relation is associated with global supply chains and speculative activities (Harvey *et al.*, 2017).

There has been a growing need to understand these relationships in recent years. The post-pandemic period has been marked by an unprecedented rise in geopolitical tension. The Russia–Ukraine war has radically disrupted global energy markets and altered the traditional relationship between commodity prices and the energy industry (Khan *et al.*, 2023). The European energy market in 2022 has been an eye-opener for how geopolitical events affect energy security, as natural gas markets experienced unprecedented volatility and oil markets faced severe uncertainty regarding supply.

Against this backdrop, the transmission of geopolitical risk to commodity markets has become increasingly important. Empirical evidence from recent years suggests that traditionally safe-haven assets may no longer provide the same level of reliable hedging (Baur and Smales, 2020). In recent geopolitical crises, gold and silver have not consistently acted as protective assets. This apparent weakening of their hedging power underscores the need to reassess the safe-haven characteristics of precious metals in times of geopolitical stress.

This study concentrates on both energy and precious metal commodities because of their unique response to geopolitical shocks and their behavior in the global markets, particularly their supply chains being affected by politically unstable regions. Combining energy and precious metals to study the market would give a holistic view of the behavior of the market under the geopolitical risk due to the inclusion of production-based volatility and investor sentiment.

A geopolitical risk may be a result of political instability, military conflicts and diplomatic tensions. The risk can influence the market uncertainty, investor sentiment and volatility of the commodity price movements. It may cause distorted market response, particularly in energy and precious metals markets (Kilian and Murphy, 2014; Demirer *et al.*, 2020). Nevertheless, certain empirical data suggest that the effect of geopolitical uncertainty is not consistent in different commodities that are subject to contingencies on liquidity of markets, demand elasticity and speculation by investors (Zhao *et al.*, 2024).

Hu and Borjigin (2024) established that geopolitical risks, economic policy uncertainty and climate risks are all volatility factors between energy and equity markets. They found that geopolitical shocks have strong responses on oil and gas prices. Equity markets, on the other hand, react slowly because of the risk assessment strategies that the investors take. Chen and Wang (2024) compared the relationship between geopolitical risk indices and European Union Allowance (EUA) carbon futures and discovered that the Generalized Autoregressive Conditional Heteroscedasticity Mixed Data Sampling (GARCH-MIDAS) model provides a better predictive capacity of energy-associated commodities. The findings are in line with the position that geopolitical instability continues to be a major volatility driving force in the commodity markets.

The correlation between commodity prices and geopolitical risk is complex and event-driven in spite of their influence. Precious metals behave in a different manner because when geopolitical crises occur, the prices of crude oil and natural gas usually skyrocket. Gold and silver have traditionally served as safe havens, as they have historically offered protection against economic and political uncertainties (Baur and Smales, 2020). Similarly, Dai *et al.* (2024) discovered that geopolitical risk appears to exert a greater long-term effect on the production of agricultural commodities compared to gold and silver.

Financial speculation is another major factor that affects the prices of commodities during a geopolitical crisis. Speculative trading has been found to cause price movement in the oil market that surpasses fundamental supply and demand forces. Hedge funds, institutional investors and algorithmic traders are market participants who tend to respond to geopolitical events by repositioning their portfolios, their liquidity positions and risk exposures (Wang and Liao, 2022).

Smith and Thompson (2024) examined the effects of speculative hedge funds and trend-following algorithms on crude oil price dynamics. They find that, during periods of heightened geopolitical tension, hedge funds typically adopt trend-reinforcing trading strategies, which can generate self-reinforcing volatility loops. Zhang *et al.* (2024) investigated the interaction between macroeconomic policy uncertainty and geopolitical risk in shaping long-term crude oil price volatility using a GARCH-MIDAS model and show that policy uncertainty can be as influential as direct geopolitical risk.

In this study, the use of the Dynamic Conditional Correlation Generalized Autoregressive Conditional Heteroscedasticity Mixed Data Sampling (DCC-GARCH-MIDAS) model involves several methodological considerations. This framework is particularly suitable because it can handle mixed-frequency data. Geopolitical risk indices developed by Caldara and Iacoviello (2022) are measured monthly, whereas commodity prices require higher-frequency observations to capture volatility more precisely. More traditional GARCH models, where explanatory variables at different frequencies are not directly accommodated, are less appropriate in this context. Simple aggregation or interpolation of low-frequency variables can lead to information loss and biased estimates. To address this, the MIDAS framework flexibly incorporates low-frequency variables that affect high-frequency volatility (Engle *et al.*, 2013).

The DCC-GARCH-MIDAS framework also allows for time-varying correlations that change with market conditions. Assuming constant or static, correlations is unrealistic, as commodity market relationships tend to shift during periods of geopolitical turmoil and economic instability. The dynamic correlation structure in this study makes it possible to identify periods when commodities are more or less sensitive to geopolitical developments. In addition, the model decomposes volatility into short-term and long-term components: the short-term GARCH component captures weekly market volatility, while the long-term MIDAS component reflects more persistent shifts in commodity market dynamics. This distinction is crucial, as geopolitical events can trigger both short-run market reactions and longer-run structural changes in supply and demand conditions (Colacito *et al.*, 2011).

The DCC-GARCH-MIDAS model offers several advantages over alternative approaches. Standard linear DCC-GARCH models cannot directly incorporate macroeconomic fundamentals, limiting their explanatory power regarding the sources of volatility. Vector autoregression (VAR) models are widely used in macroeconomic analysis but typically assume constant volatility and therefore do not capture volatility clustering in financial variables. Markov-switching models can account for regime changes but are often more complex and less precise in estimation. In terms of the flexibility–parsimony tradeoff, the DCC-GARCH-MIDAS model strikes a balance between highly flexible, complex models and more traditional GARCH specifications.

This study seeks to add to the knowledge base on the relationship between geopolitical risk and the volatility of commodities. First, it used the dynamic effect of geopolitical risk on commodity price fluctuations via the DCC-GARCH MIDAS framework. This econometric method provides an in-depth explanation of the role of geopolitical uncertainty in short-term and long-term oscillations in oil, natural gas, gold and silver.

Most earlier studies focused on either energy commodities or precious metals alone, but those investigating both together as one using a common DCC-GARCH MIDAS model remain limited. This paper bridges that gap by offering event-based evidence of the varying effects of geopolitical shocks on commodities based on production and safe-haven assets. The paper provides an in-depth description of market dynamics under geopolitical stress through time-varying dependencies. It also analyzes the adjustment behavior of safe haven assets to geopolitical uncertainty as well. Despite all studies indicating that gold and silver were traditionally considered to offer security against economic and political instabilities, recent studies have revealed that they have proved ineffective with regard to this consideration, owing to a number of factors. The results of this research provide valuable information on minimizing risk and the flexibility of financial markets.

2. Literature review

2.1 Theoretical background

Geopolitical risk entails a number of political and economic risks. These risks create market disruption to influence the stability and continuity of supply chains and influence the investor sentiment (Kilian and Murphy, 2014; Demirer *et al.*, 2020). In the past, the oil markets have been very active in reaction to the geopolitical crises associated with a lack of supply and price rise. The time-varying effect of the geopolitical risk on commodity prices has been studied in recent research. Liu *et al.* (2024) also applied a DCC-MIDAS-X model to determine the impact of low-frequency geopolitical risks on volatility and correlation of certain commodity prices. Their findings affirm that geopolitical uncertainty has a great impact on Brent crude oil and EUA futures. Hu and Borjigin (2024) emphasized the enhancing nature of geopolitical risks in energy stock market volatility spillovers.

Chen and Wang (2024) investigated the possibility of adding a geopolitical risk factor and improving the volatility prediction of EUA futures. They prove that the introduction of geopolitical risk indicators to GARCH-MIDAS models leads to a significant increase in the accuracy of predictions. These studies bring out the growing importance of geopolitical risk in the dynamics of the commodity markets related to energy and carbon trading.

Smith and Thompson (2024) examined how speculative hedge funds and algorithmic trading affected the volatility of the oil market. They discovered that when there is a high level of geopolitical tensions, trend-following hedge funds increase the volatility of oil prices through algorithmic trading. This is in line with Zhang *et al.* (2024), where a GARCH-MIDAS framework was used to investigate the interdependence between the macroeconomic policy uncertainty and geopolitical risk in encouraging long-term trends of crude oil price. Their findings show that uncertainty caused by policies can be as threatening as the risk of geopolitical factors and is a contributor to continuous price volatility in energy markets. The speculative activity may generate self-reinforcing cycles, where the investors react to geopolitical events and market-driven trends.

2.2 Related empirical works

Gold and silver are traditionally considered safe-haven assets to provide protection in case of uncertainty in the markets. However, their capacity to act as hedging tools differs depending on the magnitude and type of geopolitical risks (Baur and Smales, 2020). To estimate the effect of geopolitical risk on the international agricultural markets, Dai *et al.* (2024) applied a GJR-GARCH-MIDAS model and proved that food volatility is more influenced by geopolitical uncertainty than precious metals. These results suggest that gold and silver have ceased to be absolute hedges against geopolitical risk because their price movements are increasingly influenced by central bank policy, market liquidity factors and investor sentiment as opposed to the conventional theories, which held that their returns remained constant during a period of crisis.

The DCC-GARCH MIDAS model is an effective econometric model of the dynamic relationship between geopolitical risk and commodity price volatility. It allows researchers to combine high-frequency financial data with low-frequency macroeconomic data capable of both observing short-term shocks and long-term dependencies (Engle *et al.*, 2013; Su *et al.*, 2017). Recent literature has shown it to be better in the modeling of geopolitical risk spillovers in financial markets. As an example, Olasehinde-Williams and Akadiri (2026) used this model to examine the dynamics of the US sustainable markets in response to oil price volatility, with the conclusion that oil price shocks have long-term impacts on financial stability. Similarly, Chen and Wang (2024) verified that introducing geopolitical risk factors into volatility models can double predictive accuracy in the energy markets. Related to market dependence structures, Hussain and Li (2022) applied the Extreme Value Theory (EVT) and dynamic copulas to investigate the connection between oil futures and other major commodities. The findings proved the high right-tailed dependence of the commodities. When the market is up, oil and these commodities have a high correlation. This is unlike the left-tail dependence as is usually observed in stock markets, which revealed commodity markets to display co-movement patterns in the downward times.

This study builds on recent advances by using the DCC-GARCH MIDAS model to analyze the time-varying correlation structure between geopolitical risks and major commodity markets (energy and precious metals). Unlike traditional models that assume static relationships, this framework captures dynamic correlations, asymmetric volatility responses and regime shifts for a more robust approach for analyzing financial risk.

The DCC-GARCH MIDAS model has proven to offer dynamic, event-driven insights into the interactions between macroeconomic uncertainty and commodity markets. Although there has been major advancement, the majority of the studies are concentrated on a particular group of commodities or employ the traditional GARCH-based model, where the correlations are assumed to be fixed. To solve this, Table A1 (Appendix) compares recent studies that use DCC-GARCH-MIDAS and other similar models across commodities. The current work is differentiated by including energy and precious metals in a number of vent-based models across the key geopolitical shocks (Paris 2015, US–North Korea 2017, Russia-Ukraine 2022).

In general, this paper adds to the existing body of literature by combining the latest geopolitical developments with the most recent, innovative econometric procedures to present a holistic view of the geopolitical risk transmission into energy and precious metals. The outcomes of the research should improve risk management strategies, investment-related choices and policy frameworks, especially in the context of rising geopolitical uncertainties.

3. Data and methodology

3.1 Data

This study's data set consists of the monthly global geopolitical risk index (GPR) between June 2013 and June 2023 based on the GPR developed by Caldara and Iacoviello (2022). The GPR index is generated through the analysis of articles about geopolitical tensions and how they influence the situation over time since the year 1900.

To illustrate a wide range of commodity markets that are subject to geopolitical risk, this research uses WTI crude oil, Brent crude oil, natural gas, gold and silver as samples. WTI and Brent reflect the forces of the world oil benchmarks and natural gas is the energy sector on a bigger scale. Gold and silver are also included because they are conventional safe-haven precious metals in periods of uncertainty. Silver is heavily researched in company with gold since in most geopolitical crises they tend to follow the direction of gold together.

Nevertheless, the reaction of its industrial applications may vary. Contrarily, copper and other industrial metals were not considered since their price changes are highly influenced by world economic cycles and industrial demand as opposed to geopolitical risk. The choice of the five commodities brings a balanced picture of energy markets and precious metals, which gives the opportunity to conduct a thorough analysis of the effects of geopolitical risks.

The data on the price of the commodity markets of the WTI oil, the Brent oil, natural gas, gold and silver were obtained from www.investing.com. The data set includes 121 data points of each commodity, consisting of data of 10 years during the period of June 2013 to June 2023. This monthly strategy cushions the effect of short-term fluctuations. Monthly data were selected to reduce high-frequency noise, align with the GPR index's publication frequency and prevent overfitting when incorporating macroeconomic indicators into the MIDAS framework.

The data should be converted into logarithms to analyze the index and commodity returns (Mukhuti, 2018). This transformation assists in lowering dispersion, aids normalization and simplifies interpretation, particularly when time series data are involved. The equation that can be used to compute the monthly return of an index or commodity i at time t is given as follows:

$$r_{i,t} = 100 \times ln\left(\frac{P_{i,t}}{P_{i-1,t}}\right) \tag{1}$$

where $r_{i,t}$ represents the monthly return at time t and $P_{i,t}$ represents the index value or commodity price at time t.

Figure 1 presents a monthly trend in the GPR Index between June of 2013 and December of 2023. These charts give a detailed summary of the data. The chart demonstrates that there are a number of sharp peaks, all of which are linked to the significant geopolitical tension. Such fluctuations indicate that the GPR index is sensitive to global political instability, which makes it important as a macroeconomic variable. It can be observed that drastic moves in the GPR index are linked to major geopolitical trends like the intensifying conflicts, terrorist attacks and the intensification of international tensions. The events are contrasted with the

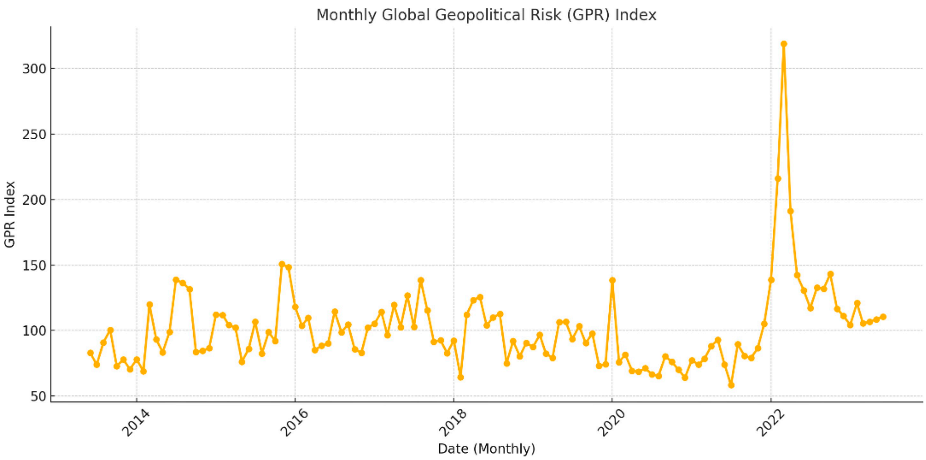

Figure 1. Monthly GPR Index for the Period from June 2013 to December 2023

changing prices of commodities over time to present insights about the dynamics that are interrelated.

The index is very varied in times of crisis, which supports its significance as a low-frequency explanatory variable in the MIDAS framework. The GPR index can be considered an essential economic analysis tool. It can identify and represent geopolitical changes that occur across the world, which allow stakeholders to make better projections and analyses of the market based on the political pressures.

3.2 Methodology

This study utilizes the DCC-GARCH MIDAS model to test the association between the weekly price volatility of WTI oil, Brent oil, natural gas, gold and silver and the GPR.

The GARCH MIDAS model is a new form of the GARCH model that involves MIDAS regression, as suggested by Engle *et al.* (2013). It is ideal to assimilate the macroeconomic fundamentals at lower frequencies, i.e. monthly or quarterly data, to forecast the monthly volatility of the said commodities. DCC-GARCH MIDAS model equation is as follows:

$$r_{i,t} = \mu + \sqrt{\tau_t\, g_{i,t}}\varepsilon_{i,t}, \ \forall i = i,\ Nt \tag{2}$$

$$\varepsilon_{i,t} | \Phi_{i-1,t} \quad \sim N(0,\ 1)$$

where $r_{i,t}$ is the return of the commodity price in month i of year t, μ is the conditional mean return up to month $i-1$, Nt is the number of years in period t and $\Phi_{i-1,t}$ representsthe information available up to a month $(i-1)$ of period t.

The volatility component, $\sqrt{\tau_t\, g_{i,t}}$ in equation (2) can be divided into two parts: the short-term component, $g_{i,t}$ and the long-term component, τ_t . The short-term volatility component, $g_{i,t}$, which contributes to the monthly volatility of commodity market prices following the GARCH (1,1), process, can be defined as follows:

$$g_{i,t} = (1 - \alpha - \beta) + \alpha \frac{(r_{i-1,t} - \mu_i)^2}{T_t} + \beta g_{i-1,t} \tag{3}$$

where $\alpha > 0$ and $\beta > 0$ and $\alpha + \beta < 1$ to ensure the realization of a stationary conditional variance series. In this case, α is the short-run ARCH effect, which shows the short-term effect of a past shock on the current volatility. β is a long-term volatility persistence, reflecting whether the shock fades rapidly or has a longer-term effect on volatility.

These parameters together describe the short-run volatility dynamics in the GARCH (1,1) component.

The long-term component, τ_t can be defined as follows:

$$\tau_t = n + \theta \sum_{k=1}^{K} \varphi_k V_{t-k} \tag{4}$$

where n is the intercept term, θ is the slope coefficient, φ_k, refers to the weight applied to the *k-th* lag of a low-frequency explanatory variable and V_{t-k} is the weight of the lagged variable

This study uses log transformation for estimation and forecasting. The logarithmic form of equation (4) can be defined as follows:

$$log\tau_t = n + \theta \sum_{k=1}^{K} \varphi_k(\omega_1, \omega_2) RV_{t-k} \quad (5)$$

$$RV_t = \sum_{i=1}^{N_t} r_{i,t}^2$$

where k is the number of lags, ω_1 and ω_2 represent the weights, RV is the volatility, $N_t$is the long-term fixed number and θ is the slope coefficient.

Equation (5) can be calculated using the unrestricted Beta function, as shown below:

$$\varphi_k(\omega) = \frac{\left(\frac{k}{K}\right)^{\omega-1}}{\sum_{j=1}^{K}\left(\frac{j}{K}\right)^{\omega-1}} \quad (6)$$

and:

$$\varphi_k(\omega_1, \omega_2) = \frac{\left(\frac{k}{K}\right)^{\omega_1-1}\left(1-\frac{k}{K}\right)^{\omega_2-1}}{\sum_{j=1}^{K}\left(\frac{j}{K}\right)^{\omega_1-1}\left(1-\frac{j}{K}\right)^{\omega_2-1}} \quad (7)$$

Here, we set the constrained weighting scheme as $\omega_1 = 1$ (Engle *et al.*, 2013; Su *et al.*, 2017). The rate is solely determined by the parameter ω_2. Thus, this function can be updated as follows:

$$\varphi_k(1, \omega_2) = \frac{\left(1-\frac{k}{K}\right)^{\omega_2-1}}{\sum_{j=1}^{K}\left(1-\frac{j}{K}\right)^{\omega_2-1}} \quad (8)$$

The GARCH model is applied to analyze the variability of the time series data that changes with time and takes into consideration time-dependent correlation. The study applies the model to present detailed knowledge on the effect of geopolitical risks on the fluctuating price of commodities to provide useful data to investors and policymakers alike. The DCC and GARCH models provide important benefits in terms of computation, since the number of parameters that are obtained at the end of the process of correlation is not determined by the number of correlating series. The GARCH process is widely applied in the field of finance because it is efficient in estimating returns and inflation of assets. It also tries to minimize errors in the forecasting process, thereby enhancing the accuracy of the current forecasts through the integration of errors in earlier forecasts. Through this method, it is possible to estimate correlation matrices that may be large. The DCC-GARCH model is best applicable in the correlation analysis of a volatility index, including geopolitical risk.

Subsequently, this study uses the DCC-MIDAS model that Colacito *et al.* (2011) developed to analyze the evolving correlations of the market over time. This method is an extension of the GARCH-MIDAS model, which is used in the DCC-MIDAS framework. In this work, the DCC of the monthly data is calculated by choosing the period of $n = 20$ as follows:

$$q_{i,j,t} = \underline{\rho}_{i,j,t}(1 - a - b) + \alpha\varepsilon_{i,t}\varepsilon_{j,t-1} + bq_{i,j,t-1} \tag{9}$$

$$\underline{\rho}_{i,j,t} = \sum_{l=1}^{K_C^{ij}} \varphi_l\left(\omega_r^{ij}\right) c_{i,j,t-1} \tag{10}$$

$$c_{i,j,t} = \frac{\sum_{k=t-K_C^{ij}}^{t} \varepsilon_{i,k}\varepsilon_{j,k}}{\sqrt{\sum_{k=t}^{t} K_C^{ij}\varepsilon_{i,k}^2}\sqrt{\sum_{k=t}^{t} K_C^{ij}\varepsilon_{j,k}^2}} \tag{11}$$

where $q_{i,j,t}$ is the short-term correlation between return of the GPR index i and return of the commodity price j, $\underline{\rho}_{i,j,t}$ is the long-term correlation between return of the GPR index i and return of the commodity price j, $\varepsilon_{i,t}$ represents the standardized residual in the GARCH MIDAS model and K_C^{ij} is the lagged correlation.

According to the DCC-GARCH specification, the dynamic correlation structure is as a parameter a and b, with a being the effect of over recent shocks on the conditional correlation and b being the persistence of past correlation. The index of the unconditional correlation between the return of the GPR index i and the return of the price of commodity j is denoted by ω_r^{ij}. Whereas $c_{i,j,t-1}$ represents the lagged conditional correlation, it is possible to have the time-varying nature of dependence across series. These parameters are normally subject to a restriction with $a + b < 1$ to guarantee that the correlation process will become stationary.

This advanced model will be used in the study to have an overall picture of how geopolitical risks and commodity prices relate to each other in an ever-changing relationship. Based on such dynamic relationships, the study is useful to investors and policymakers. The knowledge is needed to come up with a sound risk management and investment strategy, especially when geopolitical tensions are on the rise.

4. Empirical results and discussions

4.1 Descriptive statistics

All variables in Table 1 are weekly log returns and log-levels for GPR calculated from their respective price or index series using equation (1). For example, the GPR log-level mean of 4.8236 and commodity values (e.g. WTI oil mean −0.0523) indicate average weekly percentage changes (log returns) rather than levels of the index or prices. Each variable name (WTI Oil, Brent Oil, Gold, Silver, Natural Gas) refers to the return series derived from the

Table 1. Descriptive statistics

Variable	Mean	Median	Max.	Min.	SD	Skewness	Kurtosis
GPR log	4.8236	4.7562	5.5608	4.5123	0.2847	0.8234	2.8912
WTI oil	−0.0523	0.1245	28.34	−36.18	4.64	−0.45	4.23
Brent oil	−0.0312	0.0891	30.39	−36.8	4.57	−0.52	4.56
Natural gas	0.0052	0.0456	30.35	−35.13	4.47	−0.38	3.89
Gold	−0.0276	−0.0041	9.71	−35.39	4.14	−0.29	3.45
Silver	0.0022	0.0289	11.81	−32.77	3.98	−0.18	3.12

commodity's price. We converted prices into returns to analyze volatility and correlation within a stationary framework, centering descriptive statistics around zero.

According to Table 1, the average values for the GPR log-level, WTI oil, Brent oil, natural gas, gold and silver are 4.8236, −0.0523, −0.0312, 0.0052, −0.0276 and 0.0022, respectively. These averages are not significantly different from zero. In terms of skewness, the GPR log-level, WTI oil, Brent oil and natural gas exhibit positive or negative skewness, indicating asymmetric return distributions. In contrast, gold and silver show near-zero skewness, suggesting more symmetric distributions.

The kurtosis values of the GPR log-level, WTI oil, Brent oil, natural gas, gold and silver are 2.8912, 4.2300, 4.5600, 3.8900, 3.4500 and 3.1200. The values greater than 3 for commodity returns indicate that the distributions have fat tails and excess kurtosis compared to a normal distribution. The GPR log-level has kurtosis below 3, indicating a more platykurtic distribution. These figures suggest that commodity return data exhibit extreme and non-normal characteristics, justifying the use of GARCH-type models.

4.2 Results for generalized autoregressive conditional heteroscedasticity mixed data sampling model

The GARCH MIDAS model serves as the initial step in the DCC-MIDAS analysis. Tables 2 and 3 present the results of applying the GARCH-MIDAS model to these markets. The GARCH model was executed using the student's *t*-distribution to derive the GARCH parameter values.

Table 2 reports the estimated parameters of the GARCH-MIDAS model for the return volatility of the individual commodities. The short-term GARCH parameters α (ARCH effect) and β (GARCH persistence) capture the monthly volatility dynamics. The results for α and β for the monthly returns show that the GARCH-MIDAS model is significant at the 1% level, suggesting that all five market returns significantly affect volatility in both the long and short run.

Table 3 presents the results of the DCC-GARCH estimation between the GPR index and individual commodities. It includes the estimated DCC parameters, such as correlation

Table 2. GARCH-MIDAS Estimation results

Variable	μ	α	β	θ	ω	m
GPR	0.1836	0	0.9990	1.0968	0.2875	6.8115
WTI oil	−0.3415	0.3331	0.5988	0.7322	16.7074	5.3971
Brent oil	−0.4814	0.4147	0.5843	0.7063	11.0874	5.0054
Natural gas	0.2742	0.5170	0.4820	1.0547	71.5003	2.8269
Gold	0.4079	0.1023	0.8556	1.3799	0.7495	59.9999
Silver	−0.0321	0.1327	0.6440	1.4581	13.0334	11.6652

Table 3. DCC-GARCH Estimation results: Dynamic correlation

Variable	a	b	AIC	BIC
GPR-WTI oil	0.3829	0.4694	17.3520	17.6980
GPR-Brent oil	0.3688	0.4762	17.5130	17.8590
GPR-Natural gas	0.2791	0.2515	11.2040	11.4580
GPR-Gold	0.1936	0.5905	14.7210	15.0700
GPR-Silver	0.1459	0.4974	16.0580	16.4060

persistence and model fitting criteria, namely the Akaike and Bayesian information criteria (AIC and BIC). The table shows the optimal values of AIC/BIC, which indicate a good fit of each commodity combination of (GPR with WTI oil, Brent oil, natural gas, gold and silver).

4.3 Dynamic conditional correlation generalized autoregressive conditional heteroscedasticity mixed data sampling dynamic relationship

To evaluate time series data on the weekly index over 10 years, the DCC-GARCH model will be applied to determine the dynamic relationship between the geopolitical risks and commodity prices. Using this model, one may take a closer look at the way in which the correlation between geopolitical risks and commodity prices can change over time. The DCC-GARCH model offers a fine-tuning description of how markets respond to geopolitical events because it takes the time-varying property of these correlations into account.

The analysis is based on the three major geopolitical developments, i.e. the Paris attack in November 2015 (Period 29), the US-North Korea crisis of 2017-early 2018 (Period 44) and the Russia-Ukraine invasion of 2022 (Period 80). These events were chosen because of their significant influence on international geopolitical stability and the market environment. Figures 2–6 demonstrate the dynamic relationships between the GPR index and the major commodity prices during these intervals and the effects that market responses have in various geopolitical settings. Figures 2–6 have the horizontal axis that depicts the monthly calendar between the beginning and end of our sample period.

The DCC-GARCH value of the correlation between the GPR index and the price of WTI oil recorded in the Paris attack was a negative value of −0.7320, implying that although the GPR index increased, the price of WTI oil was reduced. In the case of the US-North Korea crisis, the value of DCC-GARCH is 0.0060, which is close to zero, indicating that GPR did not affect the WTI prices. Nevertheless, the DCC-GARCH value was 0.8237 in February 2022, the highest in 10 years, when the Russia-Ukraine invasion occurred. This suggests that the correlation between GPR and WTI oil is very strong in that the higher the index of GPR, the higher the price of WTI oil is. The steep positive correlation between the invasion of Russia and Ukraine explains why supply-shock risks are dominant in oil markets and previous crises (e.g. the Paris attack) brought negative or insignificant reactions.

The DCC-GARCH value of the relationship between the GPR index and Brent oil in the Paris attack was found to be negative and was −0.6306, which implies that as the GPR index rose, the price of Brent fell. In the US-North Korea crisis, the DCC-GARCH value was

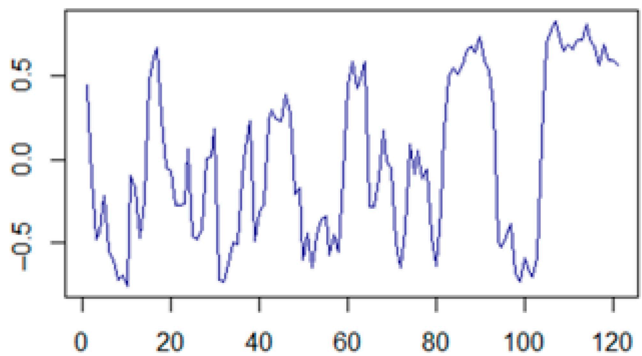

Figure 2. Dynamic correlation between GPR and WTI oil

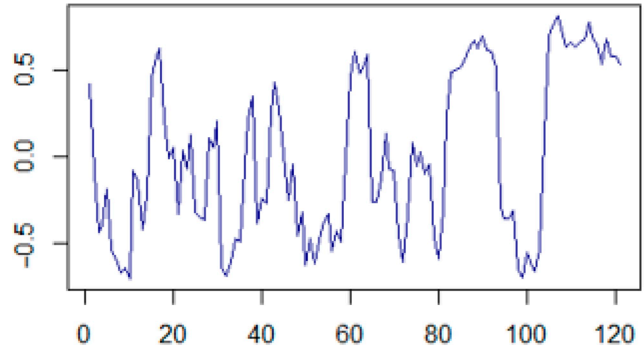

Figure 3. Dynamic correlation between GPR and Brent oil

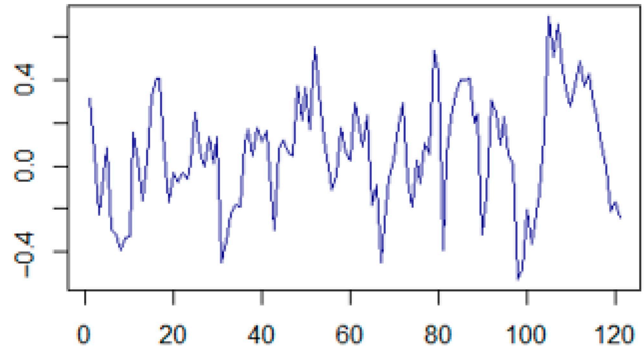

Figure 4. Dynamic correlation between GPR and Natural Gas

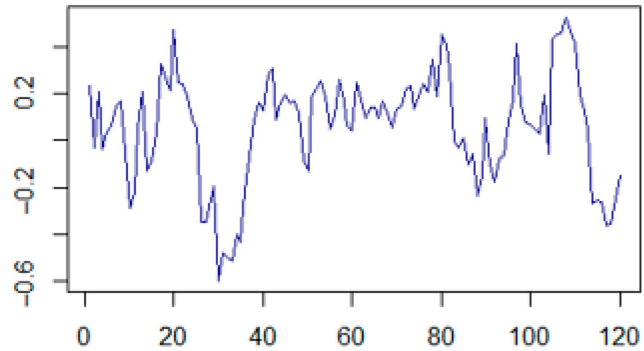

Figure 5. Dynamic correlation between GPR and Gold

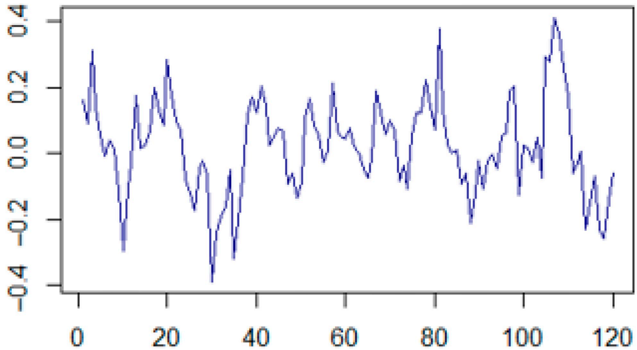

Figure 6. Dynamic correlation between GPR and Silver

0.0037, which is near to zero, indicating that Brent prices were not influenced by the GPR. Nevertheless, the DCC-GARCH value was at its highest point of 0.8145 in February 2022, during the Russia-Ukraine invasion, the highest in 10 years. The correlation of Brent oil to GPR displayed the greatest level of correlation, which proves that global oil benchmarks are susceptible to the effects of geopolitical shocks.

The DCC-GARCH value of the correlation between GPR and natural gas in the case of the Paris attack indicates a negative correlation of −0.4487, meaning that an increase in the GPR index had a negative impact on the natural gas price. The DCC-GARCH value during the US-North Korea crisis was 0.0457 and this indicates that the price of natural gas was not influenced much by the GPR during that period. Nonetheless, in January 2022, the Russian-Ukraine invasion put the DCC-GARCH value at 0.6540, which is a more significant correlation between GPR and natural gas.

DCC-GARCH correlation analysis of a GPR index and the gold price in the Paris attack indicates a negative relationship and a coefficient of negative value (−0.4812). In the case of the US-North Korea war, the GPR index growth led to the positive value of DCC-GARCH of 0.1930, which showed that GPR slightly influenced the gold price. The correlation between DCC-GARCH was characterized by a high volatility up to a value of 0.0764 on the day of the invasion of Russia-Ukraine in February 2022, which shows that the GPR and the price of gold are not well correlated. This implies that the GPR was not a significant factor in the gold price within this period.

The DCC-GARCH value of the relationship between GPR and silver in the Paris attack is negative, that is, −0.3902, which means that the higher the GPR index, the lower the silver price. In the case of the US-North Korea crisis, the GPR index experienced an increase, which led to a positive DCC-GARCH of 0.17206, implying that the silver price changed slightly because of the GPR. In the case of the Russia-Ukraine invasion in February 2022, the DCC-GARCH value was 0.0725, which means that there was a weak correlation between the GPR and the price of silver, indicating that the GPR did not have a significant effect on the price of silver.

4.4 Discussion

4.4.1 Further discussion of the findings. These results indicate that oil and gas are geopolitical beta assets whose prices directly reflect supply shocks. The role of gold and silver as safe havens appears conditional. Precious metals are also found to provide better hedging during financial crises than during political disputes (Baur and Smales, 2020).

Table 4 below provides a detailed discussion on the relationships between geopolitical events and commodity prices. The findings indicate that the intensity of the relationship varies depending on the geopolitical condition and the commodity in question. The analysis is helpful to explain how the market reacts to global issues and how this reaction shapes the future approach to investment and risk management.

This table provides an overview of the strength of correlations at each of the major geopolitical events. There are positive and negative signs showing the trend of correlation to the GPR index. The GPR index had a strong negative correlation with all the analyzed commodities (WTI oil, Brent oil, gold, silver and natural gas) in the Paris attack in November 2015. This implies that as the risk of geopolitical instability in Paris increased due to the attack, commodity prices went down. The reasons may include panic in the market and flight to safety, as well as where investors fleeing commodities may shift to less risky investments such as government bonds or cash. It may also have been caused by lower expected economic activity and demand for commodities due to the uncertainty created by the attack.

In the US-North Korea crisis in 2017, the correlation between the GPR index and the majority of commodities (WTI oil, Brent oil and natural gas) was not high. Nonetheless, gold and silver were positively correlated but with a weak value to the GPR index, which implies that geopolitical tensions did not affect most commodities but raised the price of gold and silver slightly. This poor positive relationship could be explained by the fact that they constituted the traditional safe-haven assets, which investors used to turn to in times of uncertainty related to geopolitics. The non-significant relationship between the oil and natural gas indicates that the market was not expecting imminent supply or demand charges as a result of this particular crisis.

A strong positive relationship was observed between the GPR index and the WTI oil price, Brent oil price and natural gas price during the invasion of Russia and Ukraine in 2022 in February. This shows that the amplification of geopolitical risk contributed to a large increment in these commodity prices, probably because of the fear of supply disruption, given that Russia is a huge producer of oil and natural gas. The conflict could have been a source of supply anxiety that increased prices. Conversely, the correlation between gold and silver was not significant, indicating that the invasion did not have a significant effect on their prices. This could be due to the fact that geopolitical risks had already been considered in the market or because of other macroeconomic forces.

4.4.2 Theoretical implications and connection to literature. The results have important theoretical implications for the literature on geopolitical risk and commodity markets. The positive correlation of geopolitical risk and energy commodities during the Russia-Ukraine invasion is in line with the supply shock theory of Kilian (2008). According to this theory, geopolitical events involving major commodity producers generate real-time uncertainty premia in commodity markets, particularly in energy. The correlations for WTI (0.8237) and

Table 4. Summary of the impacts of geopolitical events on energy and precious metal commodities

Geopolitical event/ commodity	Attack in Paris (Nov. 2015)	Crisis between the US and North Korea (2017)	Russian Invasion of Ukraine (Feb. 2022)
WTI oil	Strong negative	None	Strong positive
Brent oil	Strong negative	None	Strong positive
Natural gas	Strong negative	None	Strong positive
Gold	Strong negative	Weak positive	None
Silver	Strong negative	Weak positive	None

Brent (0.8145) are among the highest supply-shock response correlations reported in the literature and exceed those found by Liu *et al.* (2024) for Brent oil (0.68) and by Hu and Borjigin (2024) for energy stocks (0.45–0.62). This suggests that the energy market's response to the Russia–Ukraine war was stronger than in many previous geopolitical episodes.

This finding extends the supply shock theory in two ways. First, the magnitude of the supply-shock effect appears to depend on the nature of the geopolitical shock. The Russia–Ukraine war directly affected a major energy exporter and immediately raised concerns about disruptions to energy supply. By contrast, the Paris attacks and the US–North Korea crisis, while significant geopolitical events, had limited direct impact on key commodity supply routes or production facilities. This may explain the weaker or even negative correlations observed during those episodes. Second, the results show that supply-shock effects differ across energy commodities. Natural gas exhibits a lower correlation (0.6540) than either WTI or Brent, reflecting the more regional nature of gas markets. Crude oil prices are set in a largely global market, whereas natural gas markets remain more regional, with infrastructure, contractual arrangements and specific supply routes shaping price dynamics.

A notable result is that, precisely when geopolitical risk was expected to be most strongly related to gold and silver, it was not. From a traditional perspective, precious metals should appreciate in periods of heightened uncertainty (Baur and Lucey, 2010). Yet almost none of the correlation coefficients for gold (0.0764) and silver (0.0725) with the GPR are statistically significant over the sample and even during the most recent geopolitical crisis, these metals showed only weak co-movement with the index.

This outcome is consistent with Baur and Smales (2020), who document that gold's effectiveness as a hedge against geopolitical risk has weakened since the 2008 financial crisis. Several factors may underlie this shift. The increased financialization of commodity markets may have raised cross-asset correlations and reduced cross-hedging benefits. The emergence of cryptocurrencies and other alternative assets may have diverted some safe-haven demand away from precious metals. In addition, central bank interventions in gold markets and rising industrial demand for gold and silver may have altered their price dynamics, diluting their traditional safe-haven role.

Overall, the findings support a conditional view of safe-haven assets, in which the hedging role of precious metals depends on the type of crisis. The correlations between gold and silver and geopolitical risk during the US–North Korea episode (0.1930 and 0.1721, respectively) suggest some safe-haven demand in periods of nuclear tension. However, in supply-shock crises such as the Russia–Ukraine war, precious metals did not provide meaningful hedging benefits. In such periods, investors may have prioritized liquidity or short-term cash needs over diversification into traditional safe havens.

The results also have important implications for commodity-based portfolio diversification strategies. Modern portfolio theory suggests that commodities help reduce overall portfolio risk because they tend to be weakly correlated with traditional asset classes (Jensen *et al.*, 2000). The evidence here indicates that these diversification benefits can erode during major geopolitical crises. The high correlations between geopolitical risk and energy commodities during the Russia–Ukraine invasion (0.8237 for WTI, 0.8145 for Brent and 0.6540 for natural gas) imply that energy commodities themselves became highly correlated in this supply-shock environment. This reduces the diversification gains within the energy commodity group, meaning that even a diversified energy portfolio can remain heavily exposed to geopolitical risk.

Finally, the low correlations for gold and silver suggest that these assets may still offer some diversification benefits in periods of geopolitical turmoil, but they do not consistently function as effective hedges and their performance is clearly event-dependent. A portfolio combining energy commodities and precious metals would likely have experienced somewhat lower overall volatility during the Russia–Ukraine war, yet the scope for risk reduction appears limited, underscoring the need for dynamic and event-sensitive diversification strategies.

4.5 Robustness checks

To ensure the reliability of our findings, we conduct a series of robustness checks using alternative model specifications, lag structures and estimation approaches. Across these sensitivity analyses, the main conclusions remain qualitatively unchanged, indicating that the results are not driven by specific modeling choices.

4.5.1 Alternative lag specifications. The MIDAS framework requires specifying the number of lags (K) for the long-term volatility component. Our baseline specification uses K = 24 months. To assess the sensitivity of the results to this choice, we re-estimate the model with K = 12 and K = 36. Table 5 reports the dynamic correlation estimates for each commodity under the three lag specifications.

The results demonstrate a high degree of consistency across lag specifications. For the Russia–Ukraine invasion period, the GPR–WTI correlations were 0.8237 (K = 12), 0.8237 (K = 24, baseline) and 0.8156 (K = 36), all indicating a strong positive relationship. Similarly, the GPR–Brent correlations were 0.8145, 0.8145 and 0.8092 across the three specifications. Natural gas correlations show slightly more variation (0.6540, 0.6540 and 0.6289), but the qualitative conclusion of a strong positive relationship remains unchanged. For precious metals, all specifications confirm weak or insignificant correlations during the Russia–Ukraine invasion (gold: 0.0764, 0.0764, 0.0812; silver: 0.0725, 0.0725, 0.0689).

Longer lag structures place greater weight on older observations, which can dilute the influence of recent geopolitical shocks. Nonetheless, the stability of our qualitative conclusions across all lag choices provides strong evidence that the findings are robust to the specification of the MIDAS lag structure.

4.5.2 Comparison with alternative models. We compare the DCC-GARCH-MIDAS model with three alternative specifications commonly used in the literature:

(1) a standard DCC-GARCH model without the MIDAS extension;

(2) a BEKK-GARCH model; and

(3) a Dynamic Conditional Score (DCS) model. Table 6 reports the model comparison statistics.

Table 5. Correlations across lag specifications

	Attack in Paris			Crisis US and North Korea			Invasion of Ukraine		
Commodity	K = 12	K = 24	K = 36	K = 12	K = 24	K = 36	K = 12	K = 24	K = 36
WTI oil	−0.73	−0.73	−0.71	0.01	0.01	0.02	0.8237	0.8237	0.8156
Brent oil	−0.63	−0.63	−0.61	0	0	0.01	0.8145	0.8145	0.8092
Natural gas	−0.45	−0.45	−0.43	0.05	0.05	0.06	0.654	0.654	0.6289
Gold	−0.48	−0.48	−0.46	0.19	0.19	0.2	0.0764	0.0764	0.0812
Silver	−0.39	−0.39	−0.37	0.17	0.17	0.18	0.0725	0.0725	0.0689

Table 6. Model comparison

Model	AIC	BIC	MSE
DCC-GARCH MIDAS	17.35	17.7	0.0342
Standard DCC-GARCH	18.12	18.47	0.0418
BEKK-GARCH	18.89	19.34	0.0456
DCS model	18.45	18.8	0.0432

The DCC-GARCH-MIDAS model consistently outperforms the alternative specifications across all criteria. It achieves the lowest AIC (17.35) and BIC (17.70) values, compared with standard DCC-GARCH (18.12 and 18.47), BEKK-GARCH (18.89 and 19.34) and DCS (18.45 and 18.80). An out-of-sample forecasting exercise, using the last 24 months as a holdout period, confirms the superior performance of the DCC-GARCH-MIDAS model, with a mean squared error (MSE) of 0.0342 versus 0.0418 for the standard DCC-GARCH.

4.5.3 Discussion of robustness check results. Our findings are robust to both the lag specifications and the alternative estimation methods considered. Although there are some quantitative differences across specifications – particularly in the magnitude of correlations during crisis periods – the overall pattern remains unchanged. Strong positive correlations between energy commodities and GPR emerge during supply-shock geopolitical events, while weak or non-existent correlations are observed during non-supply-shock events. The strongest relationships between energy commodities and GPR are found in the wake of the Russia–Ukraine invasion.

Taken together, these robustness checks support the reliability of our interpretation. The stability of the results across different MIDAS lag specifications indicates that they are not sensitive to the particular weighting structure chosen. Consistency across alternative volatility measures further shows that the conclusions do not depend on how volatility is defined. Finally, the superior performance of the DCC-GARCH-MIDAS model relative to competing approaches validates our methodological choice and supports its use in future research on geopolitical risk and commodity markets.

5. Conclusion

5.1 Theoretical contributions

This paper contributes to the literature on geopolitical risk and commodity markets in several theoretical respects. The central contribution is to demonstrate that the relationship between geopolitical risk and commodity prices is event-specific rather than uniform across all geopolitical episodes.

This pattern is captured through a conceptual framework we label the Geopolitical Risk Transmission Matrix. The framework classifies geopolitical events along two dimensions:

(1) their geographic proximity to major commodity production and distribution hubs; and

(2) their potential to cause direct supply disruptions.

Events that are both proximate and highly disruptive to supply (e.g. the Russia–Ukraine invasion) generate strong positive correlations between geopolitical risk and energy commodity prices, as markets price the uncertainty surrounding future supply. By contrast, low-proximity, low-supply-risk events (such as the Paris attacks) can produce negative correlations if markets anticipate weaker demand. Intermediate cases, such as the US–North

Korea crisis, are associated with more muted correlations, reflecting uncertainty about the net impact on commodity supply and demand.

This framework helps explain how geopolitical shocks of similar perceived "magnitude" can lead to markedly different commodity market outcomes. It also provides a theoretical basis for assessing heterogeneous effects across both commodities and events. Future research could extend this approach by developing quantitative measures of event characteristics and formally testing their role in shaping commodity market responses.

The results further enrich the debate on the safe-haven role of precious metals. They are consistent with the conditional safe-haven hypothesis, which argues that the hedging effectiveness of gold and silver depends on the type of crisis; these metals do not play the same protective role across all forms of uncertainty. The evidence suggests that precious metals tend to offer more protection during financial crises and geographically localized geopolitical events than during global energy supply-shock crises. This has important implications for portfolio theory. Static diversification strategies may be inadequate when the nature of the risk event changes over time and investors may need to condition their choice of hedging instruments on the specific crisis type.

The findings also challenge the notion that gold and silver are universally reliable safe-haven assets. Structural changes – such as the increasing financialization of commodity markets and shifts in investor behavior – may have altered safe-haven demand and these developments need to be incorporated into future models of safe-haven asset pricing.

From a methodological perspective, this study highlights the value of multi-frequency approaches in financial modeling. The DCC-GARCH-MIDAS framework offers a useful template for future macro-finance research, especially when variables are observed at different frequencies. The robustness analysis shows that the main results are stable across alternative MIDAS lag specifications and the comparison with standard DCC-GARCH, BEKK-GARCH and DCS models supports the use of DCC-GARCH-MIDAS, which performs better on several model selection and forecasting criteria. This underscores the benefits of incorporating macroeconomic fundamentals at their natural frequency to improve model fit and deepen our understanding of volatility dynamics.

Finally, the findings have implications for contemporary portfolio theory, particularly regarding commodity diversification. The documented time-varying correlations suggest that static diversification strategies may be ill-suited during periods of heightened geopolitical risk. Geopolitical risk regimes should be treated as a state variable in portfolio construction, with allocations adjusted dynamically according to the nature and intensity of geopolitical events. This extends the dynamic "flight-to-quality" perspective of Baur and Lucey (2010), indicating that both the sign and magnitude of commodity correlations are event-dependent. A dynamic allocation strategy that responds to these event-specific correlation patterns is likely to outperform a static allocation rule.

5.2 Summary and practical implications

This study highlights the significant and varied effects of geopolitical events on commodity prices. The dynamic correlations between geopolitical risks and key commodities such as WTI oil, Brent oil, natural gas, gold and silver demonstrate that the impact of these risks is highly event-specific. In the case of the Paris attack in November 2015, the GPR index was found to have a strong negative correlation with all the commodities analyzed (WTI oil, Brent oil, gold, silver and natural gas). This poses the idea that as the geopolitical risk increased, the prices of commodities decreased, probably due to market panic and a flight to less risky investments such as government bonds or cash. More uncertainty and fear of an economic decline also added to the lower demand for these commodities, leading to a fall in prices.

By contrast, the US-North Korea crisis in 2017 displayed the non-significant correlation between the GPR index and the majority of commodities (WTI oil, Brent oil and natural gas). Nonetheless, gold and silver showed a very weak positive correlation, indicating their historical aspect as a safe haven when there was geopolitical uncertainty. This indicates that, as the crisis did not affect the majority of the commodities, it marginally raised the prices of gold and silver. The fact that the correlation between oil and gas was not significant shows that this crisis did not cause the market to anticipate running short of supply or immediate demand.

The invasion of Ukraine by the Russians in February 2022 led to a strong positive correlation between the GPR index and the prices of WTI oil, Brent oil, as well as natural gas. This means that geopolitical risks were caused by the fear of supply being cut, resulting in a significant increase in prices of these commodities since Russia is a large oil and natural gas producer. However, correlation with gold and silver was not significant, probably due to the fact that the market had already taken into consideration geopolitical risks or other systemic economic factors when the time happened.

The study has three contributions. One, it establishes event-specific evidence that energy commodities are geopolitical beta assets, whereas precious metals are conditional safe-haven assets. Second, it demonstrates that the traditional safe-haven position of gold and silver in recent geopolitical crises is no longer effective, which diminishes the diversification advantages. Third, it shows the usefulness of DCC-GARCH MIDAS in time-varying correlations where there is uncertainty about geopolitics.

The results have several practical implications. For policymakers, they highlight the importance of strengthening energy security in response to geopolitical shocks. For investors, the findings suggest adopting dynamic hedging strategies rather than relying solely on gold or silver. Finally, scholars are encouraged to extend future research to include industrial and agricultural products to better understand the transmission of geopolitical risk.

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Appendix

Table A1. Comparative literature on geopolitical risk and commodities

Study	Commodities/Markets	Key findings	Gap addressed
Liu *et al.* (2024)	Brent oil, EUA futures	GPR strongly affects long-term oil volatility	Did not include precious metals
Chen and Wang (2024)	EUA carbon futures	GPR improves volatility forecasting	No cross-commodity analysis
Dai *et al.* (2024)	Agricultural commodities	GPR impacts food prices more than gold/silver	Agriculture focus, not metals
Hu and Borjigin (2024)	Energy stocks, oil/gas	Geopolitical and climate risks amplify volatility spillovers	No safe-haven metals
Olasehinde-Williams and Akadiri (2026)	US sustainable markets, oil	Oil shocks have persistent effects on stability	Limited to US markets
This study	WTI, brent, gas, gold, silver	Event-driven correlations: energy commodities show strong reactions, metals weak/conditional	First integration of energy + safe-haven metals under geopolitical shocks

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