TESTING FOR REVERSE GRANGER CAUSALITY BETWEEN GEOPOLITICAL RISK AND OIL PRICES

João Pedro Lopes Teixeira Ferreira

Dissertation written under the supervision of Professor Susana Campos-Martins

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Abstract

This dissertation investigates whether geopolitical risk Granger-causes crude oil returns and volatility, or whether oil market dynamics Granger-causes geopolitical shocks. Using daily and monthly data from 1990 to 2025, this work combines a news-based index of geopolitical risk (GPR) and a market-based global common volatility measure (CoVol), alongside Brent and WTI spot prices, S&P 500 returns and the VIX as control variables.

Granger causality tests are performed at both frequencies, followed by the estimation of a parsimonious VAR model with a single lag, and is complemented by robustness checks across oil benchmarks, uncertainty measures and data frequencies.

At the daily level, Granger causality tests and VAR estimations reveal contrasting dynamics across uncertainty measures. Daily changes in geopolitical risk (GPR) do not significantly affect Brent or WTI returns, nor do oil prices feed back into geopolitical risk, reflecting the noisy and transitory nature of high-frequency news-based indicators. By contrast, oil prices and common volatility measured by CoVol SQ-1 exhibit stronger short-run interactions, with evidence of bidirectional feedback.

At the monthly horizon, geopolitical risk becomes a statistically and economically significant predictor of both Brent and WTI returns, whereas CoVol SQ-1 shows weak and benchmark-specific effects. These results highlight that geopolitical risk and market-wide volatility capture distinct dimensions of uncertainty operating at different time horizons.

Abstract português

Esta dissertação investiga se o risco geopolítico influencia os retornos do petróleo bruto ou se, inversamente, a dinâmica do mercado petrolífero gera choques geopolíticos. Utilizando dados diários e mensais entre 1990 e 2025, o estudo combina um índice de risco geopolítico baseado em notícias (GPR) com uma medida de volatilidade comum global baseada no mercado (CoVol SQ-1), juntamente com preços spot do Brent e WTI, retornos do S&P 500 e o VIX como variáveis de controlo.

São realizados testes de causalidade de Granger em ambas as frequências, seguidos da estimação de um modelo VAR parcimonioso com um único desfasamento, complementada por análises de robustez entre diferentes índices de referências de petróleo, medidas de incerteza e frequências de dados.

Ao nível diário, os resultados mostram que variações no risco geopolítico não afetam significativamente os retornos do Brent ou do WTI, nem existe evidência robusta de causalidade inversa, refletindo o carácter ruidoso e transitório dos indicadores noticiosos de alta frequência. Em contraste, observam-se interações de curto prazo mais fortes entre os preços do petróleo e a volatilidade comum global, com evidência de reciprocidade bidirecional.

No horizonte mensal, o risco geopolítico emerge como um preditor estatisticamente e economicamente significativo dos retornos do Brent e do WTI, enquanto o CoVol SQ-1 apresenta efeitos mais fracos e dependentes do índice de referência. Os resultados evidenciam que diferentes formas de incerteza operam através de mecanismos distintos e em horizontes temporais diferentes.

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Keywords: Geopolitical Risk; Common Global Volatility; Oil Market Dynamics; Vector Autoregression; Brent and WTI; Granger Causality

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Love,

João

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1. Introduction

Over the last few decades, the relationship between geopolitical risk and commodity markets, particularly crude oil, has been of both political and academic interest. As the most important and globally traded commodity, oil remains a pillar of global supply chains, macroeconomic stability, and geopolitical strategy. Its price fluctuations can trigger worldwide economic disruptions and alter geopolitical power dynamics. At the same time, oil prices themselves react sharply to changes in political stability, conflict, and uncertainty. Major historical events such as the Gulf War, the Arab Spring and, more recently, the Russian invasion of Ukraine show how geopolitical tensions can cause significant and persistent movements in oil prices and volatility.

Despite this close relationship, essential questions remain unresolved regarding the magnitude, direction and persistence of the influence that geopolitical risk has on oil markets and whether oil market dynamics themselves can change the perceptions of geopolitical uncertainty.

Due to significant progress in measuring geopolitical uncertainty, it is now easier to dive deeper into empirical analysis of these issues. Caldara, D., & Iacoviello, M. (2022) developed the Geopolitical Risk Index (GPR), a news-based measure that captures both threats and acts of geopolitical tension. More recently, Engle, R. F., & Campos-Martins, S. (2023) introduced CoVol, a market-based common-volatility measure that reflects how financial markets internalize the risk of extreme events, which turn out to be associated with the global geopolitical discourse. These measures provide the empirical foundation for testing whether geopolitical risk predicts oil price movements or whether oil market shocks drive shifts in geopolitical uncertainty.

The main objective of this dissertation is to analyze this dynamic relationship between geopolitical risk and oil market behaviour, focusing specifically on oil returns and volatility due to the geopolitical nature of the oil markets. The main research question asks whether geopolitical risk, measured by GPR or CoVol, leads to changes in oil price dynamics or whether causality flows in the opposite direction. Using econometric techniques such as Granger causality tests and Vector Autoregression (VAR), this study estimates both the short-run and persistent effects of geopolitical shocks.

The motivation for this research is both academic and practical. Rising global geopolitical tensions have heightened the need to understand how political instability and conflict influence critical commodity markets. For oil-importing and oil-exporting economies, such knowledge is essential to design stabilization policies. For investors, it helps with hedging strategies and risk management in energy-exposed portfolios. For policymakers, it provides insights into mitigating the macroeconomic consequences of geopolitical shocks.

From a methodological perspective, this dissertation follows and extends the approach of Karagozoglu, A. K., Wang, Y., & Zhou, H. (2022), who compare alternative geopolitical risk measures using a VAR framework. While their study focuses on the behaviour of the indices themselves, this dissertation applies a similar empirical structure, but to examine how geopolitical risk transmits into oil price returns. Moreover, consistent with established market-based approaches, the S&P 500 and VIX indices are incorporated as controls to capture global risk sentiment and implied uncertainty, ensuring that financial-market turbulence unrelated to geopolitical shocks is accounted for.

By integrating established geopolitical risk metrics with both daily and monthly oil price data and by analyzing returns across multiple frequencies and transformations, this dissertation contributes to the growing literature at the intersection of geopolitics, uncertainty and commodity markets. Beyond traditional geopolitical considerations, the results are also relevant in the context of climate change and the ongoing global energy transition, which have themselves become sources of geopolitical tension through shifts in energy dependence, supply-chain reconfiguration and strategic competition over critical resources. Together, these dynamics shape expectations in oil markets and reinforce the continued strategic importance of crude oil, even as economies transition toward lower-carbon energy systems.

2. Literature review

Crude oil can be susceptible to geopolitical shocks due to its centrality to global supply chains, the strategic behaviour of producing states and the importance of transport routes, (e.g. the Strait of Hormuz or the Suez Canal). Understanding how geopolitical tensions influence oil markets requires diving deeper into three primary research paths. First, the measurement of geopolitical risk and uncertainty; then, the empirical literature linking such risks to oil prices; and finally, the broader financial and macroeconomic foundations that explain how political shocks propagate into asset markets. Together, they provide a coherent theoretical and empirical basis for examining whether geopolitical risk impacts oil returns and how different risk measures, such as news-based GPR and market-based CoVol, capture these dynamics.

The modern study of uncertainty and its macroeconomic transmission begins with Bloom, N. (2009), who shows that uncertainty shocks generate abrupt surges in volatility, sharp declines in investment and hiring and a slow subsequent recovery. This framework, often referred to as the uncertainty-shock paradigm, has since become foundational for interpreting how political or geopolitical uncertainty affects fundamental and financial variables. Bloom's insights complement the work of Caldara, D., & Iacoviello, M. (2022), who introduced the Geopolitical Risk Index (GPR). This systematic, news-based measure captures threats and acts of geopolitical tension across decades. Their research demonstrates that geopolitical shocks reduce economic activity and raise financial uncertainty, providing one of the central measures used in this dissertation.

While GPR is constructed entirely from textual sources, recent literature enhances the importance of market-based indicators that capture how investors price uncertainty in real time. Engle, R. F., & Campos-Martins, S. (2023) propose CoVol, a global common-volatility measure explicitly designed to capture extreme-event risk, including geopolitical tensions. Unlike GPR, CoVol reflects how financial markets internalise and price uncertainty. This distinction between news-based and market-based uncertainty motivates the dual-measure approach of this dissertation.

Karagozoglu, A. K., Wang, Y., & Zhou, H. (2022) compare these alternative geopolitical risk measures and show that they yield different predictive dynamics for asset returns and volatility, particularly within VAR frameworks. Their findings are directly relevant to the present study, which evaluates both measures in forecasting oil market outcomes. Furthermore, this paper provides the methodological backbone of the present dissertation. Its comparative VAR framework serves as the basis for extending the analysis to the oil market rather than to risk-index interactions.

A broader conceptual perspective on geopolitics is provided by Flint, C. (2016), who contextualizes geopolitical tensions within global spatial relations, resource competition and strategic power dynamics. This view helps explain why oil markets, which are tightly linked to global trade routes, regional instability and energy security, react immediately to geopolitical shocks. Chiaramonte, L., Mecchia, F., Paltrinieri, A. & Sclip, A. (2025) provide a comprehensive survey that synthesizes the rapidly expanding literature on geopolitical risk and energy markets, documenting the persistent interdependence between geopolitical tensions, commodity prices and market volatility. Their work positions this dissertation within a rapidly evolving research current.

There is a vast body of research and empirical work on oil markets and oil prices, given their vital role in the world today. Subsequently, there also exists a substantial empirical literature examining the direct effect of uncertainty on these same topics. Early evidence comes from Aloui, R., Gupta, R., & Miller, S. M. (2016), who find that uncertainty shocks have a statistically significant impact on crude oil returns, with nonlinearities across market regimes. Antonakakis, N., Gupta, R., Kollias, C., & Papadamou, S. (2017) demonstrate that geopolitical risks shape the oil–stock nexus over more than a century, highlighting time-varying spillovers and asymmetric market responses. Mei, D., Ma, F., Liao, Y., & Wang, L. (2020) apply mixed-frequency MIDAS models and show that geopolitical uncertainty significantly increases oil futures volatility, emphasizing the importance of aligning high-frequency uncertainty measures with daily oil prices. Bouoiyour, J., Selmi, R., & Hammoudeh, S. (2019) expand this perspective by distinguishing between threats and acts of geopolitical risk, showing that these categories exert different impacts on oil prices, with threats often producing more persistent upward pressure. Zhang, Y., & Yan, X. (2020), although focused on policy uncertainty rather than geopolitical uncertainty, confirm that uncertainty shocks, whether economic or geopolitical, affect WTI oil returns differently across time and frequency domains, reinforcing the need to consider short-run versus long-run transmission mechanisms.

Several studies explicitly link conflict, terrorism and political instability to oil market outcomes. Kollias, Kyrtsou & Papadamou (2013) show that terrorism and war affects the relationship between oil prices and stock indices, showing the cross-market transmission of geopolitical shocks. Brandt, M. W., & Gao, L. (2019) apply a textual analysis to distinguish macroeconomics from geopolitical news and demonstrate that geopolitically relevant news explains a substantial share of oil price movements. Gkillas, K., Gupta, R., & Wohar, M. (2018) show that geopolitical shocks contribute to volatility jumps in oil markets, supporting the view that geopolitical uncertainty affects markets primarily through volatility channels. Chen, H., Liao, H., Tang, B.-J., & Wei, Y.-M. (2016) focus on OPEC-related political risk and, using a structural VAR, show that political instability in oil-producing countries produces significant oil price responses.

The broader literature on oil market volatility and spillovers also reinforces these mechanisms, as Hamilton, J. D. (2009) provides a foundational account of how oil price shocks, including those driven by political instability, generate macroeconomic disruptions. Conrad, C., Loch, C., & Ritter, D. (2014) show that macroeconomic uncertainty influences long-term volatility and correlations between oil and equity markets, motivating the inclusion of financial-market controls such as the S&P 500 and the VIX. Maghyereh, A. I., Awartani, B., & Bouri, E. (2016) document strong directional volatility connectedness between crude oil and equity markets, while Diaz, E. M., Molero, J. C., & de Gracia, F. P. (2016) show that oil price volatility plays a key role in shaping stock market outcomes. Apergis, N., & Miller, S. M. (2009) further demonstrate that structural oil shocks propagate into stock prices, reinforcing the importance of modelling oil within a multivariate system. Finally, Kang, W., & Ratti, R. A. (2013) identify interactions between oil shocks, policy uncertainty and stock market volatility, highlighting the broader financial-uncertainty environment in which geopolitical shocks operate.

Political risk is also studied through the lens of asset pricing. Pástor, L., & Veronesi, P. (2013) show that political uncertainty commands a risk premium and affects expected returns, while Click, R. W., & Weiner, R. J. (2009) examine the nationalism of resources and show that political risk truly impacts the valuation of petroleum reserves, offering a direct conceptual bridge between geopolitical tensions and oil-sector asset values. Through these studies, a clear theoretical foundation can be established for the hypothesis that geopolitical risk is priced into oil markets, either through expected-return channels or through volatility-risk premium.

The empirical strategy adopted in this dissertation is grounded in well-established methodological foundations. Granger, C.W.J. (1969) provides the theoretical basis for assessing directional predictability between geopolitical risk measures and oil market dynamics, offering a rigorous framework to evaluate whether information in one time series helps anticipate movements in the other. In parallel, foundational work on volatility dynamics by Engle, R.F. (2002) formalizes the view that volatility in financial and commodity markets is inherently time-varying, which is a core assumption underlying the modelling of uncertainty in this study.

Building on this, Engle, R. F., & Campos-Martins, S. (2023) formalize the use of CoVol as a market-based indicator derived from common components of global volatility and justify its use as a complementary benchmark to news-based geopolitical risk indices. Together, these foundational works provide the conceptual and statistical structure that underlies the modelling choices implemented in this dissertation.

3. Data

This chapter describes the construction of the dataset used to assess the relationship between geopolitical risk and oil market behaviour. The analysis combines news-based, market-based and macro-financial indicators. Whenever necessary, daily data is transformed into a monthly frequency using consistent averaging procedures implemented in R, ensuring comparable series across all variables. Figures 1 to 6 illustrate the history of these variables in the timeframe used for this study (1990-2025).

3.1. Sample period and data coverage

The empirical analysis is done by using daily frequency data, covering the period from the beginning of January 1990 to the end of September 2025. The choice of the temporal horizon was based on it being the maximum available period for the control variable VIX, as well as being a very robust period in terms of events that could affect the relationship between geopolitical risk and oil market behaviour. This horizon captures several major geopolitical and energy-market episodes, including the Arab Spring, 9/11, the COVID-19 pandemic, the oil prices collapse from 2014 to 2016, U.S.-Iran tensions, the Russian invasion of Ukraine in 2022 and the post-invasion reconfiguration of global energy flows. This provides a sufficiently long sample to assess the dynamic relationship between geopolitical risk and oil price behaviour.

3.2. Variables and Data Sources

The primary measure of geopolitical uncertainty is the Geopolitical Risk Index (GPR) developed by Caldara, D., & Iacoviello, M. (2022). The index was downloaded directly from Matteo Iacoviello's official website[1], which provides daily and monthly series of GPR. Their index is based on the frequency of news articles about geopolitical tensions, threats and acts of conflict across leading international newspapers. This ensures the use of a comprehensive, reproducible and academically standard measure of geopolitical risk.

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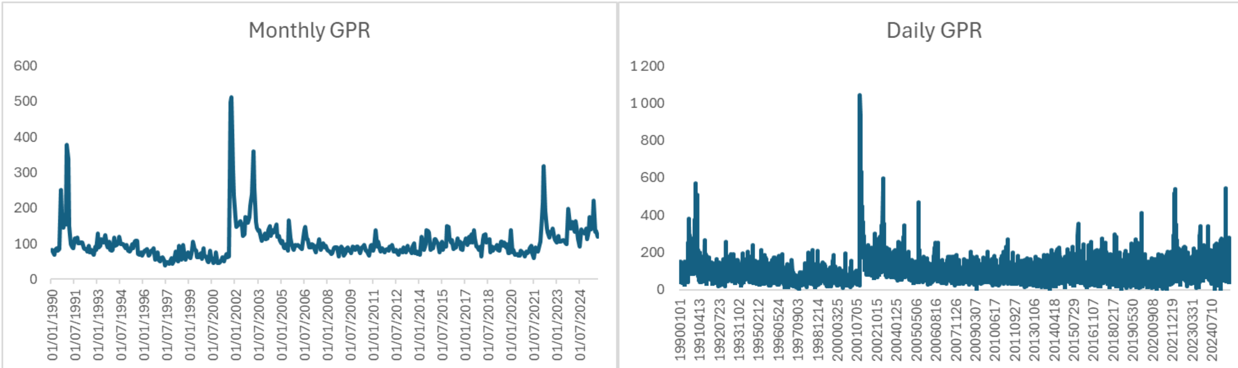
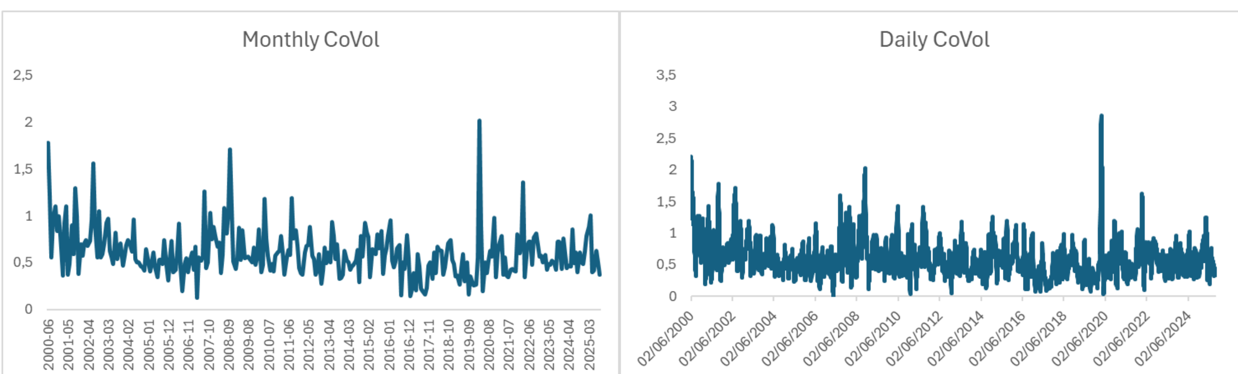
[1] https://www.matteoiacoviello.com/gpr.htm



Figures 1 and 2 - Historical values of Monthly and Daily GPR

To contrast this textual measure with a market-based proxy, the analysis also incorporates Global CoVol, developed by Engle, R. F., & Campos-Martins, S. (2023). The CoVol values were retrieved from (New York University Stern) V-Lab[2], a platform that produces daily common-volatility indicators across global financial markets. CoVol identifies episodes of synchronized global volatility and thereby serves as a complementary measure to GPR, capturing realized market stress rather than perceived geopolitical tension reflected in the news. In the case of CoVol, monthly data was not available on V-Lab. The daily values were subsequently averaged monthly.



Figures 3 and 4 - Historical values of Monthly and Daily CoVol

2 https://vlab.stern.nyu.edu/docs/covol/COVOL

Oil market data consists of daily West Texas Intermediate (WTI) and Crude Brent spot prices collected from the U.S. Energy Information Administration (EIA)[3]. The EIA is the leading public authority for U.S. and international energy statistics, ensuring accuracy and consistency. Daily returns are computed as the natural logarithm (LN) of the price ratio between consecutive trading days and multiplied by 100, which is a standard procedure when using returns. Monthly oil prices were obtained by averaging all available daily values in each month.

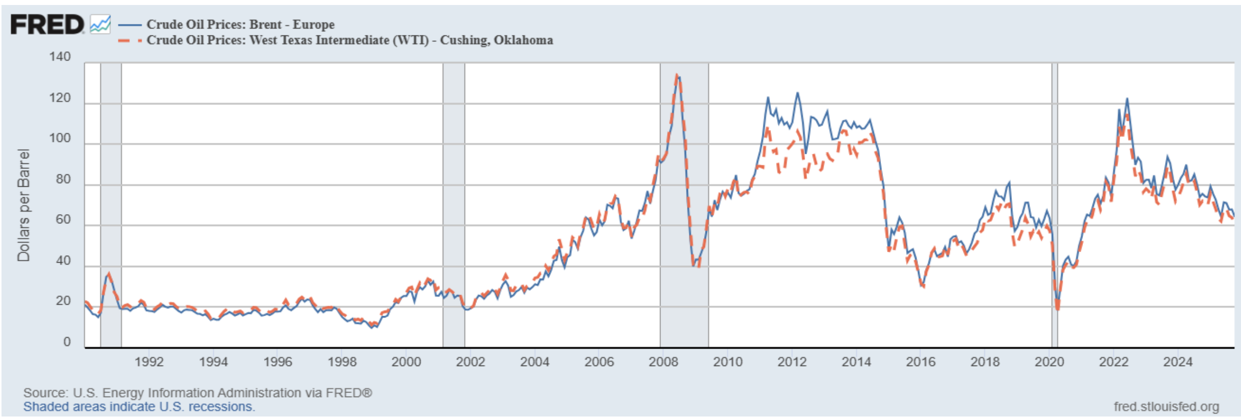


Figure 5 - Historical values of Monthly Oil Prices (Brent and WTI)

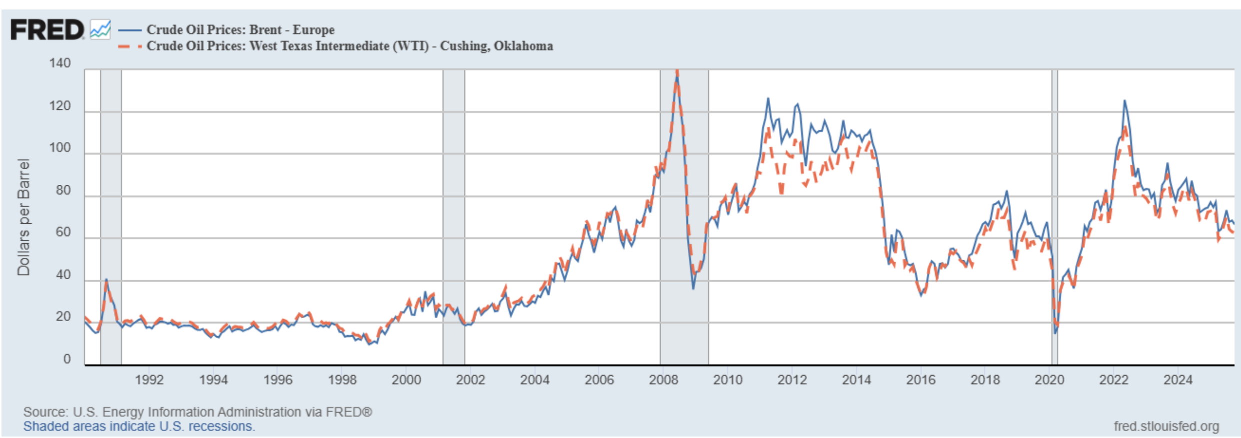


Figure 6 - Historical values of Daily Oil Prices (Brent and WTI)

Note: In April 2020, WTI's price fell into negative territory. This is not clear in the graph due to the long sample period, which compresses short-lived extreme movements.

[3] https://www.eia.gov/dnav/pet/pet_pri_spt_s1_d.htm

3.3. Control Variables: S&P 500 and the VIX

To isolate the relationship between geopolitical risk (GPR/CoVol) and oil market dynamics, the VAR specification includes two control variables: the S&P 500 index and the VIX. These variables capture broader financial and macro-uncertainty conditions that simultaneously influence both geopolitical indicators and oil prices. The S&P 500 reflects global economic sentiment and general risk-on/risk-off behaviour in equity markets. It often co-moves with oil markets, therefore, failing to condition on these movements could overstate the effect of geopolitical risk on oil returns. The VIX index measures market-implied volatility and acts as a widely recognized proxy for financial stress because it reacts almost instantly to new information. Including these controls prevents omitted-variable bias and ensures that the estimated effects of GPR and CoVol on oil prices or volatility are not confounded by underlying market conditions that move independently of geopolitical shocks. Daily S&P 500 closing prices were obtained from Refinitiv Datastream, converted to logarithmic returns and then multiplied by 100. The VIX daily values, which reflect the implied volatility of S&P 500 options, were downloaded from Yahoo Finance[4], providing reliable historical data for the CBOE Volatility Index. In both cases, monthly values were obtained by averaging all available values within a month.

3.4. Data Transformations and Statistical Treatment

Empirical analysis employs both daily and monthly frequencies.

Daily frequency

Daily data are used to compute:

- **Δ LN GPR** ⟶ log changes in GPR
- **CoVol SQ-1** ⟶ CoVol squared minus 1 (squared deviation from unity)
- **Brent/WTI Oil LN returns** ⟶ log returns for Brent/WTI oil
- **S&P 500 LN returns** ⟶ log returns for the S&P500 index
- **Δ VIX** ⟶ changes in the VIX Index

[4] https://finance.yahoo.com/quote/%5EVIX/history/

For the calculations of the LN returns, the following formula was used:

$$r_t = \ln\left(\frac{P_t}{P_{t-1}}\right)$$

, where P_t is the price at time t

These transformations ensure stationarity and allow meaningful interpretation in percentage-change terms. The daily VAR is based on daily observations and is designed to capture short-run dynamics in response to geopolitical shocks.

3.5. Monthly aggregation

For the monthly analysis, the procedure also includes averaging all daily values of the variables within each month. This procedure is applied to ensure that monthly values of these variables are a result of an average of all the daily values in a month, just like GPR – at the monthly frequency, rather than using the value on the last tradable day in any given month.

The usage of a monthly frequency VAR enables comparison with studies such as Karagozoglu, A. K., Wang, Y., & Zhou, H. (2022), which analyzes geopolitical indicators at a lower frequency to capture persistent dynamics.

The empirical specification relies on transformed rather than level variables to ensure that the time series used in the VAR model satisfies the statistical properties required for valid inference. News-based measures such as GPR and market-implied measures such as CoVol are highly persistent and often display near-unit-root behaviour in levels, which can generate fraudulent correlations in multivariate systems. The transformation of the uncertainty variables is motivated by both statistical and economic considerations. The logarithmic first difference of the Geopolitical Risk Index, Δln GPR, is employed to eliminate persistence and ensure stationarity, allowing changes in geopolitical risk to be interpreted as proportional innovations rather than movements driven by long-run trends. In contrast, CoVol is not log-differenced but transformed using its squared deviation from unity (CoVol SQ − 1), following the construction proposed by Engle, R. F., & Campos-Martins, S. (2023). This transformation captures deviations of common volatility from its long-run benchmark and isolates episodes of abnormally high market-wide stress. Unlike log-differences, the CoVol SQ-1 measure preserves the magnitude of volatility spikes and enhances sensitivity to extreme events, which are central to the interpretation of systemic uncertainty. Together, these transformations ensure stationarity while aligning the empirical specification with the distinct economic nature of news-based geopolitical risk and realized market volatility. Similarly, oil and equity markets are represented by logarithmic returns rather than levels, consistent with financial econometrics practice because price returns are stationary, scale-free, and correspond to an economically meaningful measure of market reaction.

Finally, the VIX is introduced in first differences (ΔVIX) rather than Δ ln VIX, following preliminary diagnostic tests showing that level differences produce more stable dynamics and a better model fit in the oil-return equation (higher adjusted R-squared). When taken together, these transformations ensure that all variables entering the VAR are stationary, comparable in interpretation and able to capture short-run adjustments rather than long-run trends, thereby aligning the data treatment with established practices in the geopolitical-risk and oil-market literature.

3.6. Descriptive Statistics

This section presents the descriptive statistics for all variables used in the empirical analysis, reported separately for the daily and monthly datasets. The statistics provide an initial understanding of the central tendencies, dispersion and distributional properties of the transformed time series (Δ ln GPR, CoVol SQ-1, oil returns, S&P 500 returns, and ΔVIX) that enter the VAR framework. Given the high-frequency nature of the daily dataset and the aggregation used to construct monthly values, both panels exhibit distinct distributional patterns.

Tables 1.1 and 1.2 illustrate the descriptive statistics results for the variables used in this work.

Table 1.1

Descriptive stats of used monthly variables

Variable	N	Mean	Std.Dev	Min	Median	Max	Skewness	Kurtosis
Δ LN GPR MONTHLY	429	0,000891	0,235551	-0,82567	-0,00885	2,051335	1,921302	14,30129
CoVol SQ-1 MONTHLY	304	0,006585	0,869953	-0,98472	-0,19858	7,583994	3,979635	26,0423
LN Returns Brent OIL	429	0,014963	0,581185	-5,63584	0,053751	3,338412	-1,747588	22,65528
LN Returns WTI OIL	429	0,022363	0,523852	-3,55439	0,040708	3,451748	0,253093	11,20452
LN Returns S&P500	429	0,690416	3,617049	-22,8092	1,069036	11,3529	-1,556039	7,294863
Δ VIX	429	-0,01767	4,084339	-16,2688	-0,20581	38,10787	3,083341	25,70175

Note: The variable CoVol SQ-1 MONTHLY has a smaller sample size due to limited data availability.

The monthly statistics reveal that the change in geopolitical risk (Δ ln GPR) has a mean close to zero (0.000891), as expected for a transformed, non-level index. The standard deviation of 0.235551 indicates low variability, while the distribution is notably right-skewed (skewness = 1.921302) with substantial leptokurtosis (kurtosis = 14.30129), reflecting the presence of infrequent but severe geopolitical shocks.

CoVol SQ-1 exhibits similar properties. Even though the mean is slightly greater (0,006585), the standard deviation is nearly four times higher that of Δ ln GPR one (0.869953), the distribution is even more skewed (skewness = 3,979635) and leptokurtic (kurtosis = 26,0423). Based on these statistics, both Δ ln GPR and CoVol SQ-1 are characterized by rare but extreme shocks, indicating that geopolitical and market-wide uncertainty materialize in bursts rather than gradually. However, CoVol displays substantially greater volatility and tail risk than GPR, suggesting that market-implied uncertainty reacts more violently and asymmetrically to global stress episodes than news-based geopolitical risk.

Monthly oil returns for both Brent and WTI exhibit the expected characteristics of commodity price dynamics. Brent returns show a mean of 0.014963, a standard deviation of 0.581185 and strong negative skewness (–1.747588), indicating that large negative price movements occur more frequently than large positive ones. Kurtosis is also very high (22.65528), highlighting the heavy-tailed nature of oil markets. WTI returns follow a similar pattern, with a mean of 0.022363, a standard deviation of 0.523852 and a kurtosis of 11.20452. Nevertheless, skewness is less pronounced (skewness = 0,25309).

The S&P 500 monthly returns exhibit a mean of 0.690416 and a standard deviation of 3.617049, with negative skewness (–1.556039) and elevated kurtosis (7.294863), consistent with the stylized facts of equity market returns. Changes in the VIX (ΔVIX) exhibit extreme dispersion, with a standard deviation = 4.084339 and strong right skewness (3.083341), reflecting the highly asymmetric nature of volatility spikes during periods of financial stress.

Table 1.2
Descriptive stats of used daily variables

Variable	N	Mean	Std.Dev	Min	Median	Max	Skewness	Kurtosis
Δ LN GPR DAILY	8967	6,72E-05	0,375744	-2,99588	-0,00561	2,969319	0,104407	2,071616
CoVol SQ-1 DAILY	6329	0,004595	2,29243	-0,99997	-0,99997	55,50509	8,029826	130,1479
LN Returns Brent OIL	8936	0,013206	2,566489	-64,3699	0,043459	41,20225	-1,798871	65,25754
LN Returns WTI OIL	8967	0,018798	2,668978	-40,6396	0,074766	42,58324	0,011293	27,83794
LN Returns S&P500	8967	0,032551	1,140474	-12,7652	0,058211	10,9572	-0,373181	10,88221
Δ VIX	8967	-0,00012	1,67097	-18,71	-0,07	24,86	1,367085	27,60017

Note: The variable CoVol SQ-1 DAILY has a smaller sample size due to limited data availability.

Turning to the daily dataset, the descriptive statistics show similar qualitative patterns but with higher volatility, more extreme minimum and maximum values and higher kurtosis, which are typical for high-frequency financial data such as oil returns. Daily Δ ln GPR values cluster tightly around zero (mean = 6.72×10^{-5}), yet the standard deviation (0.375744) is larger than that of the monthly series, indicating noisier high-frequency fluctuations. While skewness is mild (0.104407), the kurtosis of 2.071616 suggests the presence of occasional outliers, although less extreme than those observed in monthly data. CoVol SQ-1 values are also clustered around zero (mean = 0.004595), nevertheless, exhibiting higher dispersion (standard deviation = 2,29243), high skewness (skewness = 8,029826) and substantial kurtosis (130,1479), indicating pronounced tail risk in market-based volatility responses.

Daily oil returns for Brent and WTI exhibit extremely heavy tails, with standard deviations of 2.566489 and 2.668978, respectively, and kurtosis values of 65.25754 (Brent) and 27.83794 (WTI). These values reflect the well-documented fact that daily oil returns are far from normally distributed and often impacted by abrupt, event-driven jumps. Negative skewness is again evident in Brent (–1.798871), while WTI appears nearly symmetric (0.011293).

The S&P 500 daily returns distribution, which presents a mean of (0,032551) and a standard deviation of (1.140474) and kurtosis of (10.88221), confirms the presence of volatility clustering and extreme market movements such as those observed during the 2008 crisis and the COVID-19 shock. ΔVIX displays a mean near zero (–0.00012) but with substantial dispersion (standard deviation = 1.67097), asymmetry (skewness = 1.367085) and heavy tails (kurtosis = 27.60017), again reflecting the behaviour of implied volatility indices that tend to rise abruptly and decline gradually.

Overall, the descriptive statistics for both frequencies reveal non-Gaussian distributions characterized by high volatility, asymmetry and excess kurtosis, features that are typical for geopolitical and financial time-series. These properties justify the use of transformed stationary variables and VAR models, as the raw level series would be unsuitable for analysis due to strong persistence and risk of spurious relationships. The contrast between daily and monthly properties also supports the decision to estimate both high-frequency and low-frequency VARs, as the two datasets capture different aspects of geopolitical and financial market dynamics.

3.7. Time-series alignment and synchronization

To ensure that the regressions are estimated on a consistent and comparable dataset, all time-series were manually inspected and aligned across the daily and monthly sheets. Because each variable originates from a different source with its own trading calendar and publication schedule, several dates appeared in one series but not in others. These discrepancies were corrected by matching every observation by its date index and removing any day that did not appear simultaneously across both variables in a given regression. This manual alignment process guarantees that Δ ln GPR, CoVol SQ-1, oil returns, S&P 500 returns and ΔVIX all correspond to the same calendar day, preventing timing inconsistencies that would otherwise invalidate the VAR estimation.

The resulting dataset offers a detailed, multi-faceted view of geopolitical tensions, market-implied uncertainty, equity sentiment and oil-price behaviour. This allows for a solid empirical analysis of how geopolitical risk, whether measured textually (GPR) or through realized volatility (CoVol), influences oil markets.

4. Methodology

In this chapter, the aim is to describe the empirical strategy used to analyze whether geopolitical risk, measured through GPR or CoVol, has a Granger causal effect on oil prices or vice versa. The methodology relies on a two-equation Vector Autoregression (VAR) system estimated at both daily and monthly frequencies. The VAR approach follows the framework of Karagozoglu, A. K., Wang, Y., & Zhou, H. (2022). Still, it is adapted to the oil market by including oil logarithmic returns and financial controls such as the S&P 500 and VIX.

4.1. Conceptual Basis for the VAR Framework

The relationship between geopolitical uncertainty and oil price dynamics is inherently endogenous, characterized by simultaneity, varied reaction times and strong feedback effects. Geopolitical events can cause oil prices to fluctuate and, in contrast, sudden shifts in oil prices, especially during supply disruptions, can escalate to geopolitical tensions, particularly for countries whose financial stability relies on energy revenues. This bi-directional link justifies using a system of equations rather than a single-equation regression, which assumes unrealistic exogeneity.

A Vector Autoregression (VAR) model allows each variable to depend on its own past values and the past values of all other variables, capturing complex interactions without imposing strong theoretical restrictions. This data-driven approach is consistent with Granger, C.W.J. (1969), who emphasized predictability as the basis for causal inference. Moreover, VAR models are particularly well-suited for contexts where feedback loops and mutual dependence are expected. By accommodating bidirectional, time-varying transmission mechanisms, the VAR approach provides a flexible, empirically grounded framework for analyzing how geopolitical shocks and oil market dynamics influence one another over time.

4.2. Lag Structure in the VAR Model

The selection of the optimal lag structure for the VAR model followed the standard information-criterion approach commonly used in time-series econometrics. Using a search algorithm, the optimal lag length is assessed based on the Akaike Information Criterion (AIC), Schwarz Criterion (SC/BIC) and Hannan–Quinn Criterion (HQ), and by sequentially increasing the lag order up to a VAR(3) i.e. with three lags. Among these criteria, the Schwarz Criterion is widely regarded as the most conservative and most frequently used in empirical VAR studies because of its stronger penalty on over-parameterization, therefore favouring more parsimonious models. Across all model specifications (daily and monthly) and both geopolitical uncertainty measures (GPR and CoVol), the SC(n), where n denotes the lag order, consistently selected a one-lag VAR, except for the daily Δ ln GPR specification, where it recommended a slightly higher order. However, since the purpose of this dissertation is to compare the dynamic behaviour of multiple specifications in a consistent and methodologically coherent way and because moving from one to two lags did not significantly improve the model's fit or stability, a uniform lag length of one period was adopted for all regressions. This choice enhances comparability across models, maintains parsimony and prevents unnecessary loss of degrees of freedom.

Therefore, the VAR model was estimated using a one-period lag structure, meaning each variable is regressed on its own first lag and the first lag of the other variables. This approach assumes that effects from geopolitical shocks and market conditions emerge in the short run and that current oil price movements can be influenced by information from the previous period. Additionally, in line with existing research, oil markets and financial variables typically adjust quickly to new information, making a one-period lag sufficient to capture the key transmission mechanisms. Employing a simple lag structure ensures a well-identified model without over-parameterization. S&P500 returns and changes in the VIX are also included with one lag to mitigate contemporaneous endogeneity and to condition the VAR dynamics on prior financial market conditions.

4.3. VAR Model Specification

VAR System Representation

The system can be written as:

$$\begin{aligned}\Delta \ln(GPR)_t &= \alpha_1 + \beta_{11}\Delta \ln(GPR)_{t-1} + \beta_{12} r_{t-1}^{OIL} + \gamma_{13} r_{t-1}^{S\&P} + \gamma_{14}\Delta VIX_{t-1} + \varepsilon_{1t}, \\ r_t^{OIL} &= \alpha_2 + \beta_{21}\Delta \ln(GPR)_{t-1} + \beta_{22} r_{t-1}^{OIL} + \gamma_{23} r_{t-1}^{S\&P} + \gamma_{24}\Delta VIX_{t-1} + \varepsilon_{2t}.\end{aligned}$$

Where the two equations are estimated simultaneously.

Equation 1: Δ ln GPR or CoVol SQ-1 as the dependent variable

$$\Delta \ln (GPR)_t \text{ or } (\text{CoVol SQ-1})_t$$

It is regressed on:

- $\Delta \ln (GPR)_{t-1}$ or $(\text{CoVol SQ} - 1)_{t-1}$
- ln S&P 500 returns $_{t-1}$
- ln oil returns $_{t-1}$
- Δ (VIX) $_{t-1}$

Where t in this case can be either a day or a month

This equation tests whether oil price movements can predict next-day geopolitical shocks, while controlling for overall market stress and past geopolitical shocks.

Equation 2: Oil log returns as the dependent variable

$$r_t^{OIL} = \ln (P_t/P_{t-1})$$

It is regressed on:

- $\Delta \ln (GPR)_{t-1}$ or $(\text{CoVol SQ} - 1)_{t-1}$
- ln oil returns $_{t-1}$
- ln S&P 500 returns $_{t-1}$
- Δ (VIX) $_{t-1}$

This equation tests whether geopolitical shocks can predict next-day oil price movements, while controlling for overall market stress and past oil behaviour.

The key coefficients of interest for this empirical study are the cross-variable lag coefficients. In the first equation, β_{12} measures the effect of lagged oil returns on geopolitical risk, capturing the Oil-to-GPR transmission channel. In the second equation, β_{21} represents the effect of lagged geopolitical risk on oil returns, corresponding to the GPR-to-Oil transmission channel. Both constitute the core mechanism examined in this thesis.

4.4. Robustness Checks

To strengthen the model and ensure reliable results for this dissertation, several robustness checks are included to confirm that specific modelling choices do not influence the baseline results. With the application of these checks, the findings remain consistent across all alternative specifications, confirming the reliability of the estimated relationship between geopolitical risk and oil returns. The robustness checks include: Alternative Geopolitical Measures, Different Oil Price Benchmarks, Data Frequency Robustness and Lag-Length Robustness.

Starting with alternative geopolitical measures, the VAR model is re-estimated using CoVol SQ-1 instead of the news-based GPR index. Then, to ensure that the choice of oil market does not influence the results, the analysis is repeated using both WTI and Brent prices. Brent is the leading benchmark for European and international crude markets, while WTI reflects conditions in the North American market. Using both benchmarks allows the model to account for potential regional differences in pricing dynamics, transportation issues and inventory shocks. The consistent results across Brent and WTI confirm that the relationship between geopolitical risk and oil markets is not specific to a single regional benchmark.

As previously mentioned, the baseline results are based on daily data, but the analysis is also repeated using monthly observations. Including a lower-frequency specification acts as a robustness check by testing whether the identified relationships stay consistent when short-term noise is smoothed out and broader market trends become more noticeable. Using different frequencies helps to understand to what extent the empirical findings are driven by the high frequency of the baseline dataset and that the dynamics between geopolitical risk and oil markets are affected by the chosen data frequency.

Finally, an additional robustness check concerns the choice of lag length in the VAR model system. To verify that the baseline specification uses an appropriate and statistically supported lag length, VAR models have been estimated for different lag orders and evaluated using standard information criteria, as explained above. This validation provided a statistical robustness check that the chosen lag length is not arbitrary but supported by formal model-selection criteria, ensuring the stability and interpretability of the estimated VAR dynamics.

5. Results

This chapter presents the empirical results of the study, starting with an assessment of causal relationships between geopolitical uncertainty and oil market behaviour using Granger causality tests. These tests offer an initial indication of whether fluctuations in geopolitical risk, measured through GPR or CoVol, contain predictive information about future movements in oil returns or if oil market changes help explain upcoming shifts in geopolitical indicators. Determining the direction of predictability is a key first step, as it influences the interpretation of the subsequent VAR results and helps establish whether the relationship is one-way, two-way, or not statistically significant. After analyzing causality patterns at both daily and monthly levels, the chapter examines the complete set of VAR estimations.

5.1. Granger Causality Results

The first step in analyzing the dynamic relationship between the geopolitical risk index (GPR) and the oil markets is to assess whether changes in geopolitical uncertainty help predict future oil price movements or if oil returns contain predictive information for upcoming variations in geopolitical risk. Therefore, a Granger causality test is performed for both monthly and daily data, using WTI and Brent returns separately. The results offer an initial insight into the direction of predictability before moving on to the VAR analysis. The complete set of results is reported in the *Appendix (Tables 2.1-2.16)*, to avoid overloading the main text with additional statistical output.

Before proceeding with the empirical results, it is essential to clarify the hypotheses underlying the Granger causality tests. For each pair of variables, the null hypothesis (H_0) states that past values of variable X do not help predict variable Y. In contrast, the alternative hypothesis (H_1) indicates that X Granger-causes Y by providing incremental predictive information beyond Y's own history. These hypotheses are tested in both directions, from geopolitical risk (GPR or CoVol) to oil returns and from oil returns to geopolitical risk, to assess whether the predictive relationship is unidirectional, bidirectional, or absent.

As shown in the *Appendix Tables* 2.1-2.4, for the monthly frequency, the test examining whether monthly changes in log GPR predict WTI returns shows an F-statistic of 3.973 with a p-value of 0.047. At the 5% significance level, this indicates that monthly changes in the log geopolitical risk index (Δ ln GPR) Granger-causes monthly WTI oil returns, suggesting that geopolitical news provides additional predictive information for oil price movements at lower frequencies. In contrast, the reverse test, whether WTI oil returns Granger-cause changes in log GPR, results in a p-value of 0.262, well above the typical significance threshold of 0.05. This implies that, at the monthly level, WTI oil returns do not significantly explain subsequent changes in log GPR. A similar pattern is observed with Brent oil. Brent oil returns do not Granger-cause Δ ln GPR (p-value = 0.175), but Δ ln GPR does Granger-cause Brent oil returns, with an F-statistic of 4.225 and a p-value of 0.040. Overall, these findings suggest a one-way monthly causal relationship from geopolitical risk to oil markets, supporting the idea that major geopolitical events influence oil prices, but oil price movements do not substantially affect the GPR index.

The daily results, shown in the *Appendix Tables* 2.5-2.8, vary significantly, reflecting the higher noise and rapid adjustments typical of high-frequency financial data. For Brent, the test to determine whether daily changes in log GPR predict daily oil returns shows a p-value = 0.223, indicating no statistically significant causality. The reverse direction is also not significant (p-value = 0.247), suggesting that neither variable can daily forecast the other. The WTI results also support this conclusion. Δ ln GPR does not Granger-cause WTI returns (p-value = 0.556), and daily WTI returns only show marginal, statistically insignificant predictive power for GPR (p-value = 0.065). Although the latter nears the 10% significance level, it remains outside standard thresholds and does not provide strong evidence of causality.

Taken together, the Granger causality tests indicate that the predictive relationships between geopolitical risk and oil markets appear to depend on the frequency of the data. At the monthly level, the geopolitical risk index (GPR) consistently Granger-causes oil returns (for both Brent and WTI), supporting the idea that geopolitical events influence oil markets once short-term noise is smoothed out and more lasting information becomes evident. However, at the daily level, the lack of statistically significant causality in either direction suggests that high-frequency oil prices are mainly driven by the market's quick information processing, microstructure noise and short-term fluctuations, offering little evidence of systematic predictability from geopolitical factors. These findings justify using the VAR model at both frequencies to better understand how oil returns respond dynamically to geopolitical shocks.

Looking at the Granger causality tests conducted, using CoVol as the measure of geopolitical and systemic uncertainty, they provide a complementary perspective on whether market-implied volatility pressures help predict oil price movements or whether oil market fluctuations propagate back into global volatility conditions.

For the monthly frequency, the Granger causality tests reported in *Appendix Tables 2.9–2.12* provide no strong evidence of predictive relationships between CoVol SQ-1 and oil price returns. In the case of Brent, the null hypothesis that CoVol SQ-1 does not Granger-cause monthly oil returns cannot be rejected, with an F-statistic of 1.227 and a p-value of 0.269. Similarly, the reverse causality test yields an F-statistic of 0.027 and a p-value of 0.870, indicating no evidence that Brent returns predict CoVol SQ-1 at the monthly horizon. These results suggest an absence of directional predictability between market-wide volatility and Brent oil returns at lower frequencies.

When considering monthly WTI returns, the evidence remains weak. The test examining whether CoVol SQ-1 Granger-causes WTI returns produces an F-statistic of 3.281 with a p-value of 0.071, which is marginally significant at the 10% level, but not at conventional 5% thresholds. The reverse test shows no evidence of causality from WTI returns to CoVol SQ-1, with an F-statistic of 0.423 and a p-value of 0.516. Overall, the monthly results indicate that any predictive relationship between CoVol and oil prices is weak and sensitive to the chosen benchmark, with only limited evidence for WTI at lower significance levels.

At the daily frequency, the results in *Appendix Tables 2.13–2.16* reveal a markedly different pattern. For Brent, there is strong bidirectional Granger causality. CoVol SQ-1 significantly predicts daily Brent returns, with an F-statistic of 9.250 and a p-value of 0.002. Conversely, Brent returns also Granger-cause changes in CoVol SQ-1, as indicated by an F-statistic of 16.859 and a p-value of 0.00004. This suggests an active feedback mechanism between market-wide volatility and Brent prices at high frequencies.

A similar bidirectional relationship is observed for daily WTI returns. The test for CoVol SQ-1 predicting WTI returns yields an F-statistic of 4.161 and a p-value of 0.041, indicating statistical significance at the 5% level. The reverse causality is even stronger, with WTI returns Granger-causing CoVol SQ-1 (F-statistic of 27.686, p-value $\approx$ 0.000). These findings imply that short-run oil price movements, particularly for WTI, contain substantial information about subsequent shifts in global market co-movement, while changes in CoVol also exert predictive power over daily oil returns.

Taken together, the Granger causality results point to a frequency-dependent relationship between common global volatility and oil markets. At the monthly level, evidence of causality is weak and largely absent, whereas at the daily frequency, strong bidirectional predictability emerges for both Brent and WTI. This pattern suggests that interactions between oil prices and global financial volatility are primarily short-run phenomena, consistent with rapid information transmission, financialization of oil markets and feedback effects between commodity prices and broader market uncertainty.

These findings contrast with the results obtained for the geopolitical risk index (GPR). In the case of GPR, when statistically significant, causality tends to run from geopolitical risk to oil markets at the monthly frequency, supporting the view that geopolitical tensions influence oil prices through slower-moving, expectation-driven channels. By contrast, the CoVol results indicate that common global volatility and oil price movements are primarily linked in high-frequency (daily) contexts. Moreover, the direction of causality in these cases often reflects feedback effects from oil markets into broader volatility conditions, rather than a purely exogenous transmission of uncertainty shocks into oil prices. This distinction highlights that different measures of uncertainty capture different economic mechanisms and operate over different time horizons.

Before turning to the full set of VAR estimations, it is useful to reflect on the implications of the Granger causality tests for the modelling strategy. The initial analysis considered both daily and monthly frequencies. For GPR, the Granger tests reveal that predictive relationships with oil returns emerge mainly at the monthly frequency, while daily interactions are statistically insignificant. This pattern is consistent with the noisy and highly transitory nature of daily GPR fluctuations, which makes it difficult for high-frequency data to capture the gradual transmission of geopolitical information into oil prices. As a result, monthly aggregation helps isolate the more persistent component of geopolitical risk, strengthening the economic interpretability of the results.

In contrast, the Granger causality tests based on CoVol point to an opposite frequency profile. At the monthly level, there is little evidence of systematic predictability between CoVol and oil returns for either Brent or WTI. However, at the daily frequency, strong bidirectional causality emerges for both benchmarks, indicating rapid feedback between oil price movements and market-wide volatility conditions. This suggests that CoVol primarily captures short-run financial stress and market co-movement effects, which are transmitted quickly and are closely intertwined with oil price dynamics at high frequencies.

Taken together, these results motivate the use of VAR models at both frequencies, but for different analytical purposes. Monthly VARs are better suited to examining the effects of geopolitical risk shocks, which operate through slower and more persistent channels. Daily VARs, on the other hand, are particularly relevant for capturing the fast-moving interactions between oil prices and global financial volatility as measured by CoVol. By estimating VAR systems at both horizons, the analysis aligns the econometric framework with the underlying economic mechanisms suggested by the Granger causality evidence, thereby enhancing the robustness and interpretability of the empirical findings.

Progressing now to the VAR models, the results are structured to reflect this sequential empirical exercise. Therefore, it will start with the regressions where GPR daily is used and then move to the monthly results.

5.2. Daily VAR Systems: GPR and Oil Returns

The analysis begins with the use of daily data in the VAR framework, to capture the short-run transmission of geopolitical shocks into oil prices. Using daily observations allows the model to capture the high-frequency nature of news releases, market reactions and volatility adjustments, under the assumption that geopolitical events, particularly when unexpected, can generate immediate responses in oil markets. This approach seeks to identify whether geopolitical tensions exert measurable same-day or next-day effects on oil returns and whether financial stress indicators, such as the VIX and equity market movements (S&P 500), act as rapid transmission channels. In other words, this daily VAR is designed to test fast-moving causal dynamics that could otherwise be obscured at lower frequencies.

Tables 3.1 and 3.2 present the results of the VAR model, namely the estimates from GPR Daily with the two oil benchmarks.

Table 3.1

VAR_model GPR BRENT DAILY

	Dependent variable: com Δ VIX	
	Y	
	Δ LN GPR DAILY	LN Returns Brent OIL
Δ LN GPR DAILY $_{t-1}$	-0.440***	-0.089
	(0.009)	(0.072)
LN Returns Brent OIL $_{t-1}$	0.002	0.006
	(0.001)	(0.011)
LN Returns S&P500 $_{t-1}$	0.008	0.049
	(0.005)	(0.038)
Δ VIX $_{t-1}$	0.014***	-0.032
	(0.003)	(0.026)
const	-0.0002	0.012
	(0.004)	(0.027)
Observations	8,935	8,935
R^2	0.196	0.002
Adjusted R^2	0.195	0.001
Residual Std. Error (df = 8930)	0.337	2.565
F Statistic (df = 4; 8930)	543.003***	4.180***
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table 3.2

VAR_model GPR WTI DAILY

	Dependent variable: com Δ VIX	
	Y	
	Δ LN GPR DAILY	LN Returns WTI OIL
Δ LN GPR DAILY $_{t-1}$	-0.433***	-0.036
	(0.010)	(0.076)
LN Returns WTI OIL $_{t-1}$	0.003**	-0.020*
	(0.001)	(0.011)
LN Returns S&P500 $_{t-1}$	-0.0003	-0.045
	(0.005)	(0.039)
Δ VIX $_{t-1}$	0.008**	-0.075***
	(0.003)	(0.027)
const	-0.0003	0.021
	(0.004)	(0.028)
Observations	8,966	8,966
R^2	0.189	0.001
Adjusted R^2	0.189	0.001
Residual Std. Error (df = 8961)	0.336	2.665
F Statistic (df = 4; 8961)	522.809***	3.226**
Note:	*p<0.1; **p<0.05; ***p<0.01	

Regression 1: Δ ln GPR Daily and Brent Returns Daily

Addressing Table 3.1 in the Δ ln GPR daily equation, the autoregressive coefficient is strongly negative and highly significant (–0.440), with a SE = 0.009 and a p-value < 0.01, indicating extremely rapid mean reversion in daily changes in GPR. This suggests that when there is a positive change in GPR in one day, the following day will have a negative change, which will revert the value of GPR closer to its original value. This behaviour is typical of daily fluctuations in news-based indices, where spikes are often short-lived and revert quickly.

Looking now at lagged Brent returns, the coefficient is positive albeit statistically insignificant (0.002, SE = 0.001) for predicting changes in log GPR, reinforcing the finding that oil market movements do not seem to influence geopolitical risk. S&P500 returns also don't show any significance. In contrast, ΔVIX enters with a significant positive coefficient in this equation, at the 5% significance level.

Turning to the Brent returns equation, Δ ln GPR is not statistically significant (–0.089, SE = 0.072). This indicates that geopolitical shocks do not translate into next-day oil price reactions.

Instead, the transmission mechanism appears to operate at a lower frequency, consistent with the idea that market participants may incorporate geopolitical information with a lag. Both the S&P500 returns and ΔVIX are also insignificant.

Regression 2: Δ ln GPR Daily and WTI Returns Daily

Turning the attention to Table 3.2, the Δ ln GPR equation mirrors, in some respects, the previous regression. A strongly negative autoregressive term (–0.433, SE = 0.010, $p < 0.01$) confirms fast mean reversion. The coefficient attached to the lagged WTI returns is also positive, but significant at the 5% level (0.003, SE = 0.001), suggesting that, in this case, WTI returns from the previous day can marginally predict changes in geopolitical risk.

In the WTI returns equation, Δ ln GPR remains statistically insignificant (–0.036, SE = 0.076). Thus, as for Brent, daily geopolitical risk shocks do not translate into measurable same-day WTI price movements. Conversely, WTI returns display their own dynamics through the significant autoregressive term in daily returns (–0.020, SE = 0.011, $p < 0.1$), which may reflect microstructure noise or temporary price corrections.

5.3. Daily VAR Systems: CoVol and Oil Returns

Because CoVol is inherently a high-frequency measure derived from realized market volatility, it is particularly informative to examine its dynamics at daily frequency. These daily VAR systems provide insight into how quickly shocks to global market volatility transmit to oil prices and vice versa, and whether such transmissions differ from those observed using daily GPR, since one is a news-based index and the other is a market-based one.

Tables 3.3 and 3.4 present the results of the VAR model, namely the estimates from CoVol Daily with the two oil benchmarks.

Table 3.3
VAR model CoVol BRENT DAILY

	Dependent variable:	
	Y	
	CoVol SQ-1 DAILY	LN Returns Brent OIL
CoVol SQ-1 $_{t-1}$	0.192*** (0.013)	-0.035** (0.015)
LN Returns Brent OIL $_{t-1}$	-0.032*** (0.011)	-0.023* (0.013)
LN Returns S&P500 $_{t-1}$	-0.162*** (0.036)	0.092** (0.042)
Δ VIX $_{t-1}$	-0.001 (0.024)	-0.031 (0.028)
const	0.008 (0.028)	0.012 (0.033)
Observations	6,328	6,328
R^2	0.052	0.005
Adjusted R^2	0.052	0.004
Residual Std. Error (df = 6323)	2.232	2.626
F Statistic (df = 4; 6323)	87.114***	7.949***
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table 3.4
VAR model CoVol WTI DAILY

	Dependent variable:	
	Y	
	CoVol SQ-1 DAILY	LN Returns WTI OIL
CoVol SQ-1 $_{t-1}$	0.193*** (0.012)	-0.020 (0.015)
LN Returns WTI OIL $_{t-1}$	-0.042*** (0.010)	-0.039*** (0.013)
LN Returns S&P500 $_{t-1}$	-0.174*** (0.037)	-0.048 (0.046)
Δ VIX $_{t-1}$	-0.019 (0.025)	-0.098*** (0.031)
const	0.004 (0.028)	0.025 (0.034)
Observations	6,344	6,344
R^2	0.054	0.004
Adjusted R^2	0.053	0.003
Residual Std. Error (df = 6339)	2.218	2.719
F Statistic (df = 4; 6339)	90.031***	6.115***
Note:	*p<0.1; **p<0.05; ***p<0.01	

Regression 3: CoVol SQ-1 Daily and Brent Returns Daily

In Table 3.3, the autoregressive term in the CoVol SQ-1 daily equation is positive and highly statistically significant (0.192, SE = 0.013, $p < 0.01$). This finding contrasts sharply with the strong negative autoregressive behaviour observed for Δ ln GPR in the daily regressions. The positive coefficient indicates that increases in CoVol SQ-1 tend to persist over time: higher realized common volatility today is likely to be followed by elevated volatility tomorrow. This dynamic is fully consistent with the well-documented phenomenon of volatility clustering, where periods of significant/small price changes follow periods of significant/small price changes (either positive or negative). Unlike news-based geopolitical indicators, market-based volatility measures evolve smoothly and accumulate through sustained episodes of financial turbulence.

Lagged Brent returns enter the CoVol SQ-1 equation with a small but statistically significant negative coefficient (–0.032, SE = 0.011, $p < 0.01$), suggesting that negative oil price movements marginally increase subsequent market-wide co-movement. S&P 500 returns also enter with a negative and statistically significant coefficient (–0.162, SE = 0.036, $p < 0.01$), reinforcing the interpretation of CoVol SQ-1 as a financial-market-driven indicator: equity market declines are associated with higher realized common volatility. ΔVIX is statistically insignificant in this equation, likely reflecting the overlap in the information captured by implied volatility and realized volatility measures at the daily frequency.

Turning to the Brent oil returns equation, CoVol SQ-1 enters with a negative and statistically significant coefficient (−0.035, SE = 0.015, $p < 0.05$), indicating that increases in market-wide realized volatility are associated with lower next-day Brent returns. This pattern is consistent with risk-off dynamics, where heightened financial stress reduces demand for cyclical assets and commodities, placing downward pressure on oil returns. Lagged Brent returns are weakly significant and negative (–0.023, SE = 0.013, $p < 0.10$), suggesting mild short-term correction dynamics. S&P 500 returns are positive and statistically significant (0.092, SE = 0.042, $p < 0.05$), indicating that oil prices tend to rise following equity market recoveries. ΔVIX remains insignificant in this equation.

Regression 4: CoVol SQ-1 Daily and WTI Returns Daily

The CoVol SQ-1 equation closely mirrors the dynamics observed in the Brent specification. The autoregressive coefficient is again positive and highly significant (0.193, SE = 0.012, $p < 0.01$), confirming strong persistence in common volatility. This reinforces the interpretation of CoVol SQ-1 as a measure dominated by volatility clustering rather than mean reversion.

Lagged WTI returns enter the CoVol SQ-1 equation with a negative and statistically significant coefficient (–0.042, SE = 0.010, $p < 0.01$), suggesting that declines in WTI prices contribute to higher subsequent market-wide volatility. S&P 500 returns also exert a negative and highly significant effect (–0.174, SE = 0.037, $p < 0.01$), again highlighting the strong link between equity market conditions and realized common volatility. ΔVIX remains statistically insignificant, consistent with the Brent-based results.

In the WTI returns equation, CoVol SQ-1 is statistically insignificant (–0.020, SE = 0.015), indicating that daily fluctuations in realized market-wide volatility do not meaningfully predict next-day WTI price movements. However, WTI returns exhibit pronounced short-run correction dynamics: the autoregressive coefficient is negative and highly significant (–0.039, SE = 0.013, p

< 0.01), consistent with market microstructure effects and temporary price overshooting. ΔVIX enters with a negative and statistically significant coefficient (–0.098, SE = 0.031, $p < 0.01$), suggesting that increases in implied volatility are associated with lower next-day WTI returns, reflecting risk-off behaviour in energy markets.

Leading Into the Need for Monthly Analysis

Taken together, the daily VAR systems, whether based on Δ ln GPR or CoVol SQ-1 and whether using Brent or WTI returns, indicate that the transmission of uncertainty shocks to oil prices at the daily horizon is limited and highly fragmented. While certain financial variables and autoregressive terms display statistical significance, the core relationship of interest (namely the effect of geopolitical risk or common volatility shocks on daily oil returns) remains weak and economically small. Daily changes in GPR exhibit strong mean reversion, reflecting the noisy and transitory nature of news-based measures at high frequency, whereas daily movements in CoVol SQ-1 capture broad market volatility dynamics that are not systematically translated into crude oil price adjustments within a one-day window.

These results suggest that daily frequency data may be ill-suited to capture the economic mechanisms through which geopolitical tensions and uncertainty affect oil markets. The channels through which geopolitical risk influences oil prices, such as revisions in expectations about supply disruptions, precautionary demand, strategic inventory decisions, and risk premium, are inherently slow-moving and unlikely to materialize instantaneously. Consequently, any meaningful impact of uncertainty on oil prices is more likely to emerge over longer horizons, once high-frequency noise is smoothed out and persistent information accumulates.

For this reason, the analysis proceeds with a monthly frequency VAR framework. Monthly aggregation reduces the influence of short-term volatility and microstructure effects, allowing the model to better capture the medium-term transmission of geopolitical and uncertainty shocks into oil price dynamics.

5.4. Monthly VAR Systems: GPR and Oil Returns

Tables 3.5 and 3.6 present the results of the VAR model, namely the estimates from GPR Monthly with the two oil benchmarks.

Table 3.5
VAR_model GPR BRENT MONTHLY

	Dependent variable:	
	Y	
	Δ LN GPR MONTHLY	LN Returns Brent OIL
Δ LN GPR MONTHLY $_{t-1}$	-0.161***	0.274**
	(0.048)	(0.119)
LN Returns Brent OIL $_{t-1}$	0.035	0.034
	(0.021)	(0.052)
LN Returns S&P500 $_{t-1}$	0.002	-0.011
	(0.005)	(0.012)
Δ VIX $_{t-1}$	0.004	-0.027**
	(0.004)	(0.011)
const	-0.001	0.021
	(0.012)	(0.029)
Observations	428	428
R^2	0.032	0.036
Adjusted R^2	0.023	0.027
Residual Std. Error (df = 423)	0.233	0.574
F Statistic (df = 4; 423)	3.511***	3.942***
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table 3.6
VAR_model GPR WTI MONTHLY

	Dependent variable:	
	Y	
	Δ LN GPR MONTHLY	LN Returns WTI OIL
Δ LN GPR MONTHLY $_{t-1}$	-0.159***	0.209*
	(0.048)	(0.108)
LN Returns WTI OIL $_{t-1}$	0.032	0.135***
	(0.023)	(0.052)
LN Returns S&P500 $_{t-1}$	0.002	0.001
	(0.005)	(0.011)
Δ VIX $_{t-1}$	0.004	0.003
	(0.004)	(0.010)
const	-0.001	0.018
	(0.012)	(0.026)
Observations	428	428
R^2	0.030	0.024
Adjusted R^2	0.021	0.015
Residual Std. Error (df = 423)	0.233	0.520
F Statistic (df = 4; 423)	3.309**	2.614**
Note:	*p<0.1; **p<0.05; ***p<0.01	

Regression 5: Δ ln GPR Monthly and Brent Returns Monthly

The first equation in Table 3.5 presents the results of Δ ln GPR as the dependent variable and shows a strongly negative and highly statistically significant autoregressive coefficient (–0.161, SE = 0.048, $p < 0.01$). This implies mean reversion in the month-to-month changes of GPR, consistent with the high persistence of news-based indices documented in Caldara, D., & Iacoviello, M. (2022). The fact that Δ ln GPR reverts toward zero indicates that geopolitical shocks, although potentially large, tend to be followed by partial corrections in the subsequent month.

Lagged Brent returns appear insignificant (0.035, SE = 0.021) to explain changes in GPR, suggesting that monthly oil price behaviour does not influence the news flow or the frequency of geopolitical tensions captured by the GPR index. Likewise, S&P500 returns and ΔVIX also appear statistically insignificant. This aligns with GPR's conceptual nature as a news-based indicator rather than a financial-market-driven variable.

The second equation has Brent oil as the dependent variable. Here, Δ ln GPR enters with a positive and statistically significant effect (0.274, SE = 0.119, $p < 0.05$). This indicates that increases in geopolitical risk are associated with higher Brent oil returns in the following month.

The direction of the effect is consistent with the behaviour expected under heightened geopolitical tensions, where precautionary demand, supply disruption fears and higher risk premiums translate into upward pressure on oil prices.

Lagged Brent returns (0.034, SE = 0.052) again show no evidence of momentum or reversal at the monthly horizon. Notably, ΔVIX exhibits a negative and statistically significant effect (–0.027, SE = 0.011, $p < 0.05$), implying that increases in expected future financial market stress reduce next-month Brent returns.

Regression 6: Δ ln GPR Monthly and WTI Returns Monthly

The Δ ln GPR equation in Table 3.6 shows a negative, highly significant autoregressive coefficient (–0.159, SE = 0.048, $p < 0.01$), reinforcing the mean-reverting nature of monthly changes in geopolitical risk. Lagged WTI returns (0.032, SE = 0.023) remain statistically insignificant, just as for Brent returns in Regression 5, confirming that monthly oil price movements, regardless of the benchmark, do not influence the evolution of GPR.

In the WTI returns equation, Δ ln GPR has a positive and statistically significant effect (0.209, SE = 0.108, $p < 0.1$). Although the significance level is slightly weaker than in the Brent equation, the direction and interpretation are both consistent. Geopolitical risk shocks are associated with higher oil returns the next month. This reinforces the notion that geopolitical uncertainty is a priced factor in crude oil markets, even when using a regionally specific benchmark such as WTI.

Lagged WTI returns (0.135, SE = 0.052, $p < 0.01$) are significant in this regression, suggesting modest momentum in monthly WTI performance. This may reflect inventory cycles, transportation constraints or regional storage dynamics in the U.S. crude oil market. ΔVIX, however, is statistically insignificant in this regression, suggesting that monthly WTI returns may be less sensitive than Brent returns to broader global risk-aversion shocks. S&P500, as in the Brent oil regression, is also statistically insignificant.

5.5. Monthly VAR Systems: CoVol and Oil Returns

After looking at a news-based index (GPR), it is now time to look at a market-based index (CoVol). Because CoVol is inherently more volatile and more tightly linked to financial market dynamics than GPR, differences between the monthly VARs of GPR and CoVol provide insight into whether the source of geopolitical uncertainty, news-based vs market volatility-based, relates to crude oil prices in distinct ways.

Tables 3.7 and 3.8 present the results of the VAR model, namely the estimates from CoVol Monthly with the two oil benchmarks.

Table 3.7
VAR model CoVol BRENT MONTHLY

	Dependent variable:	
	Y	
	CoVol SQ-1 MONTHLY	LN Returns Brent OIL
CoVol SQ-1 $_{t-1}$	-0.035 (0.085)	0.069 (0.059)
LN Returns Brent OIL $_{t-1}$	0.047 (0.097)	-0.028 (0.067)
LN Returns S&P500 $_{t-1}$	-0.012 (0.021)	-0.009 (0.015)
Δ VIX $_{t-1}$	0.013 (0.020)	-0.045*** (0.014)
const	0.006 (0.051)	0.019 (0.035)
Observations	303	303
R^2	0.007	0.051
Adjusted R^2	-0.006	0.038
Residual Std. Error (df = 298)	0.867	0.602
F Statistic (df = 4; 298)	0.552	3.973***
Note:	$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$	

Table 3.8
VAR model CoVol WTI MONTHLY

	Dependent variable:	
	Y	
	CoVol SQ-1 MONTHLY	LN Returns WTI OIL
CoVol SQ-1 $_{t-1}$	-0.045 (0.084)	0.137** (0.053)
LN Returns WTI OIL $_{t-1}$	-0.035 (0.104)	0.122* (0.066)
LN Returns S&P500 $_{t-1}$	-0.013 (0.021)	0.009 (0.014)
Δ VIX $_{t-1}$	0.009 (0.021)	-0.013 (0.013)
const	0.008 (0.051)	0.018 (0.032)
Observations	303	303
R^2	0.007	0.034
Adjusted R^2	-0.006	0.021
Residual Std. Error (df = 298)	0.867	0.549
F Statistic (df = 4; 298)	0.523	2.585**
Note:	$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$	

Regression 7: CoVol SQ-1 Monthly and Brent Returns Monthly

In the CoVol SQ-1 equation in Table 3.7, in contrast to the daily specification, the monthly CoVol SQ-1 equation does not display statistically significant autoregressive dynamics. The coefficient on lagged CoVol SQ-1 is negative and statistically insignificant (–0.035, SE = 0.085), indicating that, at the monthly horizon, changes in realized common volatility do not exhibit systematic mean reversion or persistence once financial controls are included. This result suggests that the strong volatility clustering observed at daily frequency largely dissipates when volatility is aggregated to a monthly scale.

Lagged Brent returns enter the CoVol SQ-1 equation with a positive but statistically insignificant coefficient (0.047, SE = 0.097), implying that monthly oil price movements do not contribute meaningfully to subsequent changes in global market-wide volatility. Similarly, S&P 500 returns do not exert a statistically significant effect (–0.012, SE = 0.021), indicating that broad equity market performance does not materially influence monthly CoVol dynamics once higher-frequency effects are smoothed out. ΔVIX is also statistically insignificant in the CoVol SQ-1 equation, suggesting that short-run implied volatility shocks do not translate directly into month-to-month changes in realized common volatility.

Turning to the Brent returns equation, CoVol SQ-1 enters with a positive but statistically insignificant coefficient (0.069, SE = 0.059). This finding indicates that monthly changes in realized market-wide volatility do not predict next month's Brent oil returns. This result stands in sharp contrast to the GPR-based monthly VAR systems, where geopolitical risk exhibited a clear and significant positive effect on oil prices. The insignificance of CoVol SQ-1 implies that broad financial volatility does not transmit into oil markets through the same channels as geopolitical tensions. Notably, ΔVIX enters the Brent returns equation with a negative and highly statistically significant coefficient (–0.045, SE = 0.014, $p < 0.01$), consistent with risk-off behaviour: increases in financial market stress depress oil returns in the subsequent month.

Regression 8: CoVol SQ-1 Monthly and WTI Returns Monthly

As in the Brent specification, the CoVol SQ-1 equation shows no significant autoregressive behaviour. The coefficient on lagged CoVol SQ-1 is negative but statistically insignificant (–0.045, SE = 0.084), confirming that monthly CoVol dynamics do not exhibit meaningful persistence or reversion. Lagged WTI returns are also insignificant (–0.035, SE = 0.104), reinforcing the conclusion that oil price movements do not influence subsequent realized market-wide volatility at the monthly horizon. S&P 500 returns and ΔVIX remain statistically insignificant.

The WTI returns equation, however, reveals one notable difference relative to the Brent system. Lagged CoVol SQ-1 enters with a positive and statistically significant coefficient (0.137, SE = 0.053, $p < 0.05$), indicating that increases in realized market-wide volatility are associated with higher WTI returns one month later. This effect may reflect precautionary demand or inventory-related adjustments specific to the U.S. oil market, where volatility spikes could be interpreted as signals of future supply uncertainty or macro-financial stress that raise expected returns. Lagged WTI returns are also positive and weakly significant (0.122, SE = 0.066, $p < 0.10$), suggesting modest monthly momentum in WTI prices. By contrast, S&P 500 returns and ΔVIX remain statistically insignificant in the WTI returns equation, implying that broader financial conditions exert a weaker direct influence on WTI than on Brent at the monthly horizon.

5.6. Discussion

This dissertation sets out to examine whether geopolitical and common volatility-related shocks influence crude oil price dynamics and, crucially, whether the nature of risk and the temporal frequency at which it is measured, matter for detecting such effects. By jointly analyzing a news-based geopolitical risk index (GPR) and a market-based volatility measure (CoVol SQ-1) across daily and monthly frequencies, the empirical results reveal a clear and coherent pattern: the transmission of uncertainty into oil prices is both frequency-dependent and measure-specific.

A first key insight emerges from the daily VAR systems. On the daily horizon, neither geopolitical risk shocks nor market-wide volatility shocks generate strong or systematic effects on crude oil returns. Daily changes in GPR exhibit pronounced and rapid mean reversion, reflecting the noisy and transitory nature of high-frequency news-based indices. Spikes in geopolitical news coverage tend to be short-lived and are quickly corrected, limiting their capacity to influence oil prices within a one-day window. As a result, daily GPR shocks fail to predict either Brent or WTI returns. Also, oil price movements do not meaningfully feed back into changes in geopolitical risk.

The daily results using CoVol SQ-1 reinforce this conclusion, albeit through a different mechanism. Unlike GPR, CoVol SQ-1 displays strong persistence at daily frequency, consistent with volatility clustering in financial markets. This confirms that CoVol SQ-1 captures sustained episodes of market-wide stress rather than isolated shocks. However, despite this persistence, daily fluctuations in common volatility do not translate into systematic oil price adjustments. While some limited effects appear in specific specifications, such as a modest negative association between CoVol SQ-1 and next-day Brent returns, the overall evidence indicates that broad financial volatility does not serve as a dominant driver of daily oil price movements. Instead, oil markets appear largely insulated from high-frequency volatility shocks, reacting more strongly to oil-specific fundamentals and market microstructure dynamics.

Taken together, the daily VAR evidence suggests that high-frequency data are ill-suited to capture the economic channels through which geopolitical risk and uncertainty affect oil markets. The mechanisms linking geopolitical tensions to oil prices, (expectations of supply disruptions, precautionary demand, strategic inventory decisions and risk premium) are unlikely to materialize within a single trading day, particularly when the underlying uncertainty measures are either excessively noisy (GPR) or overly broad (CoVol SQ-1).

This motivates the transition to a monthly frequency framework, where the results change considerably. On the monthly horizon, geopolitical risk measured through GPR emerges as a statistically and economically meaningful predictor of oil returns. In both Brent and WTI specifications, increases in monthly GPR are associated with higher oil returns in the subsequent month. This finding supports the view that geopolitical tensions are gradually priced into oil markets as expectations about supply risks, transportation disruptions and geopolitical instability evolve over time. Monthly aggregation smooths out short-term noise in the GPR series and allows its persistent component to exert a measurable influence on price formation.

By contrast, the monthly VAR systems based on CoVol SQ-1 paint a different picture. Once volatility is aggregated to a monthly scale, CoVol SQ-1 loses the strong persistence observed at daily frequency and does not consistently predict oil returns. For Brent, realized common volatility remains unrelated to subsequent price movements, even though financial stress, captured by ΔVIX, exerts a negative effect consistent with risk-off behaviour. For WTI, a positive association between lagged CoVol SQ-1 and oil returns emerges, but this effect is benchmark-specific and weaker than the GPR-based results. Overall, the monthly evidence suggests that market-wide volatility shocks may transmit into oil prices in some markets but not others.

The contrast between GPR and CoVol SQ-1 highlights a central conceptual distinction. GPR captures geopolitical narratives that are directly relevant for oil markets, particularly because oil production and transportation are geographically concentrated in politically sensitive regions. As such, GPR conveys information about future supply risks and geopolitical uncertainty that is explicitly priced into crude oil markets over medium-term horizons. CoVol SQ-1, on the other hand, captures broad financial turbulence driven by a wide range of macroeconomic and market forces, many of which are unrelated to oil-specific fundamentals. While CoVol SQ-1 is informative about financial stress, it does not consistently translate into oil price dynamics in the same way as geopolitical risk.

Differences between oil benchmarks further reinforce this interpretation. Brent, which reflects global pricing conditions and incorporates geopolitical developments in major exporting regions, such as Europe, Africa and the Middle East, exhibits slightly stronger and more consistent reactions to GPR shocks than WTI. WTI, being more regionally anchored, as the name states, Western Texas, and influenced by U.S. specific storage and transportation dynamics, shows weaker and less robust responses. Although most newspapers used to create the GPR index are North American, they report globally, not only American news but also global news. This makes it understandable as to why a global benchmark such as Brent can still exhibit stronger and more consistent reactions to a mostly U.S made index, than a U.S oil benchmark. Although both benchmarks exhibit sensitivity to GPR at the monthly horizon, Brent's response is generally stronger, reflecting its closer exposure to global geopolitical developments. The more limited and benchmark-specific effects observed for CoVol SQ-1 underline that oil markets differentiate between geopolitical uncertainty that threatens physical supply and general financial volatility that reflects broader market stress.

Across all specifications, the role of financial controls provides additional clarity. Equity market returns and implied volatility significantly explain CoVol SQ-1 dynamics, confirming its financial-market-driven nature, but they have little explanatory power for GPR, reinforcing its exogeneity. This asymmetry further supports the interpretation that GPR and CoVol SQ-1 capture fundamentally different dimensions of uncertainty, only one of which is systematically relevant for oil price formation.

Overall, the results lead to three main conclusions. First, geopolitical risk influences oil markets primarily at lower frequencies, where persistent information and expectation-driven mechanisms dominate. Second, market-wide volatility does not play a comparable role, despite its importance for financial markets more broadly. Third, the choice of uncertainty measure and data frequency is crucial. Relationships that are invisible at daily horizons become evident once uncertainty is measured appropriately and allowed to accumulate over time. These findings highlight the importance of distinguishing between different forms of uncertainty when analyzing commodity markets and provide a clearer understanding of how geopolitical tensions are transmitted into oil prices.

6. Conclusion

The empirical analysis carried out in this chapter shows that the impact of uncertainty on oil markets depends critically on both the frequency of the data and the way risk is measured. At daily frequency, news-based geopolitical risk (Δ ln GPR) does not exert a statistically significant influence on Brent or WTI returns, reflecting the noisy and rapidly mean-reverting nature of high-frequency geopolitical news. In contrast, market-based common volatility (CoVol SQ-1) exhibits strong bidirectional Granger causality with both Brent and WTI at the daily frequency, indicating rapid informational feedback between oil prices and broader financial volatility conditions. However, the corresponding VAR estimates show that these interactions translate into only limited and benchmark-dependent effects on oil returns, suggesting that while daily common volatility and oil prices are closely intertwined through short-run financial market dynamics, this relationship does not constitute a strong or systematic transmission channel for oil price formation.

When the analysis shifts to monthly data, a different pattern emerges. Geopolitical risk measured through Δ ln GPR becomes a statistically significant predictor of oil returns for both Brent and WTI, consistent with the idea that geopolitical tensions are gradually priced into crude oil markets through expectations of supply disruptions and risk premium. By contrast, CoVol SQ-1 does not consistently predict monthly oil returns when the benchmark selected is the Brent, but it shows a benchmark-specific and weaker predictive effect for WTI, suggesting that broad financial volatility can play a more limited role in oil price formation at lower frequencies. Overall, these findings indicate that geopolitical risk affects oil markets primarily at medium-term horizons, while common global volatility affects mainly high-frequency settings, highlighting the importance of both the uncertainty proxy and data frequency when analyzing oil price dynamics.

7. Limitations

Despite the robustness of the empirical framework, this dissertation is subject to several limitations that should be acknowledged.

First, the analysis relies on a reduced-form VAR with a single lag, chosen for parsimony and comparability reasons across specifications. While this approach facilitates interpretation, it may overlook longer-term dynamics or more complex propagation mechanisms that unfold beyond a one-period horizon. Similarly, including only two financial control variables (the S&P 500 and the VIX) captures broad market sentiment but cannot fully account for all macroeconomic and financial forces that influence oil markets.

A second limitation arises from the data and frequency choices. Although the transition from daily to monthly data was necessary to extract meaningful information from the geopolitical risk index, monthly aggregation inevitably smooths short-lived shocks and may obscure intra-month dynamics that can be relevant. Moreover, the analysis is based solely on spot prices for Brent and WTI. While spot prices are widely used benchmarks, they do not fully capture market expectations, forward-looking risk premiums, or hedging behaviour that are embedded in futures markets.

There are also conceptual limitations related to the uncertainty risk measures employed. The GPR index, though widely used, reflects media coverage rather than objective geopolitical conditions and may be sensitive to changes in journalistic behaviour or reporting volume. CoVol, on the other hand, captures realized common volatility across markets but may be too broad to isolate oil-specific sources of risk and uncertainty. Both measures, therefore, come with interpretative limitations that must be considered when drawing conclusions.

Finally, the VAR model used in this dissertation provides only linear, average effects and cannot distinguish between different types of geopolitical shocks, such as supply-side conflicts, diplomatic tensions or terrorist events, which may have heterogeneous impacts on oil markets. Nor does it allow for nonlinearities, asymmetric reactions or regime changes, all of which are well documented in energy economics.

While these limitations do not undermine the validity of the empirical findings, they highlight methodological and conceptual dimensions that future research could address to deepen our understanding of the geopolitical oil price nexus.

8. Future Research

While the empirical analysis presented in this dissertation provides clear evidence regarding the role of geopolitical risk in shaping oil market dynamics, several avenues remain open for further research.

First, although the present study adopts a parsimonious one-lag VAR structure, supported by information criteria and the need for model comparability, future work could explore alternative lag specifications or higher-order VAR models to determine whether longer adjustment horizons reveal additional transmission channels between geopolitical risk and oil prices. Similarly, the set of control variables could be expanded. In this dissertation, the S&P 500 and the VIX serve as broad proxies for global financial conditions. Still, future studies may incorporate alternative or complementary indicators such as interest rate spreads, the dollar index or measures of macroeconomic uncertainty.

A natural extension involves testing the role of Economic Policy Uncertainty (EPU), as developed by Baker, S. R., Bloom, N., & Davis, S. J. (2016). Since EPU captures policy-driven ambiguity rather than conflict-based geopolitical tensions, comparing its predictive power with GPR and CoVol could yield valuable insights into whether oil markets react differently to political versus economic forms of uncertainty.

When adopting GPR, the index can be further decomposed into GPR Acts and GPR Threats. This distinction allows researchers to isolate whether markets react more strongly to realized geopolitical events (Acts) or to anticipatory tensions and warnings (Threats), which often generate more persistent uncertainty. By separating these components, future studies can identify asymmetric market responses, uncover different volatility transmission channels and improve the precision of forecasting models for oil returns and volatility.

Another promising direction concerns the choice of oil price benchmarks. While this dissertation focuses on spot prices for Brent and WTI, incorporating futures prices may help capture forward-looking expectations that are not fully reflected in spot markets. A futures-based study could also assess whether geopolitical shocks induce changes in convenience yields, risk premiums or hedging pressures along different maturities.

Finally, future research could benefit from exploring alternative econometric frameworks. Structural VARs, Bayesian VARs, nonlinear or regime-switching models, or high-frequency identification techniques may provide deeper insights into the heterogeneity of geopolitical shocks and their market impacts. Machine learning methods for textual analysis or mixed-frequency MIDAS regressions could also be used to better integrate daily news signals with monthly or low-frequency market behaviours.

Taken together, these extensions would not only refine and contextualize the findings of this dissertation but also contribute to a more comprehensive understanding of how geopolitical and financial uncertainty propagates through global energy markets.

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Appendix

Table 2.1

Granger Causality Test: Δ Ln GPR Monthly causes Ln Returns BRENT OIL

F- STATISTIC	1	4.225
P-value	1	0.040

Note: H1: P-value < 0.05

Table 2.2

Granger Causality Test: Ln Returns BRENT OIL causes Δ Ln GPR Monthly

F- STATISTIC	1	1.847
P-value	1	0.175

Note: H1: P-value < 0.05

Table 2.3

Granger Causality Test: Δ Ln GPR Monthly causes Ln Returns WTI OIL

F- STATISTIC	1	3.973
P-value	1	0.047

Note: H1: P-value < 0.05

Table 2.4

Granger Causality Test: Ln Returns WTI OIL causes Δ Ln GPR Monthly

F- STATISTIC	1	1.264
P-value	1	0.262

Note: H1: P-value < 0.05

Table 2.5

Granger Causality Test: Δ Ln GPR Daily causes Ln Returns BRENT OIL

F- STATISTIC	1	1.487
P-value	1	0.223

Note: H1: P-value < 0.05

Table 2.6

Granger Causality Test: Ln Returns BRENT OIL causes Δ Ln GPR Daily

F- STATISTIC	1	1.343
P-value	1	0.247

Note: H1: P-value < 0.05

Table 2.7

Granger Causality Test: Δ Ln GPR Daily causes Ln Returns WTI OIL

F- STATISTIC	1	0.346
P-value	1	0.556

Note: H1: P-value < 0.05

Table 2.8

Granger Causality Test: Ln Returns WTI OIL causes Δ Ln GPR Daily

F- STATISTIC	1	3.395
P-value	1	0.065

Note: H1: P-value < 0.05

Table 2.9

Granger Causality Test: CoVol SQ-1 Monthly causes Ln Returns BRENT OIL

F- STATISTIC	1	1.227
P-value	1	0.269

Note: H1: P-value < 0.05

Table 2.10

Granger Causality Test: Ln Returns BRENT OIL causes CoVol SQ-1 Monthly

F- STATISTIC	1	0.027
P-value	1	0.870

Note: H1: P-value < 0.05

Table 2.11

Granger Causality Test: CoVol SQ-1 Monthly causes Ln Returns WTI OIL

F- STATISTIC	1	3.281
P-value	1	0.071

Note: H1: P-value < 0.05

Table 2.12

Granger Causality Test: Ln Returns WTI OIL causes CoVol SQ-1 Monthly

F- STATISTIC	1	0.423
P-value	1	0.516

Note: H1: P-value < 0.05

Table 2.13

Granger Causality Test: CoVol SQ-1 Daily causes Ln Returns BRENT OIL

F- STATISTIC	1	9.250
P-value	1	0.002

Note: H1: P-value < 0.05

Table 2.14

Granger Causality Test: Ln Returns BRENT OIL causes CoVol SQ-1 Daily

F- STATISTIC	1	16.859
P-value	1	0.00004

Note: H1: P-value < 0.05

Table 2.15

Granger Causality Test: CoVol SQ-1 Daily causes Ln Returns WTI OIL

F- STATISTIC	1	4.161
P-value	1	0.041

Note: H1: P-value < 0.05

Table 2.16

Granger Causality Test: Ln Returns WTI OIL causes CoVol SQ-1 Daily

F- STATISTIC	1	27.686
P-value	1	0.00000

Note: H1: P-value < 0.05