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“An econometric analysis of the oil futures market and the role of geopolitical risk”

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Abstract

This study investigates the impact of geopolitical risk (GPR) on the oil market for the period between January 1986 and May 2022. Although many studies have presented results on this topic, they were conducted before the year 2019 without taking into consideration the extreme events that took place during the COVID-19 pandemic. By using recent data, it is examined whether the relationship between oil prices and GPR changed over time and how the market is responding to geopolitical risk after accounting for COVID-19. A structural vector autoregressive (SVAR) model was developed to study the impact of GPR on oil futures using four variables: global oil supply, global oil demand, the crude oil futures basis and geopolitical risk.

The main results of the study show that the crude oil futures basis has a significant positive response to increased geopolitical risk. However, no direct impact of geopolitical risk to oil supply and demand was found. The results suggest that economic and political uncertainty have an influence on the anticipation for future changes in oil availability. It can be argued that market participants expect a disruption in oil supply as a result of developments that disturb geopolitical stability.

Keywords: *geopolitical risk, oil futures, SVAR model*

Περίληψη

Η παρούσα μελέτη διερευνά τον αντίκτυπο του γεωπολιτικού κινδύνου (GPR) στην αγορά πετρελαίου για την περίοδο μεταξύ Ιανουαρίου 1986 και Μαΐου 2022. Παρ' όλο που πολλές μελέτες έχουν παρουσιάσει αποτελέσματα σχετικά με το συγκεκριμένο θέμα, πραγματοποιήθηκαν πριν από το έτος 2019 χωρίς να λάβουν υπόψη τα ακραία γεγονότα που έλαβαν χώρα κατά τη διάρκεια της πανδημίας COVID-19. Με τη χρήση πρόσφατων δεδομένων, εξετάζεται κατά πόσον η σχέση μεταξύ των τιμών του πετρελαίου και του γεωπολιτικού κινδύνου μεταβλήθηκε με την πάροδο του χρόνου και πώς ανταποκρίνεται η αγορά στον γεωπολιτικό κίνδυνο λαμβάνοντας υπόψιν και την περίοδο του COVID-19. Για τη μελέτη της επίδρασης του γεωπολιτικού κινδύνου στα συμβόλαια μελλοντικής εκπλήρωσης επί του πετρελαίου, αναπτύχθηκε ένα διαρθρωτικό διανυσματικό αυτοπαλίνδρομο υπόδειγμα (SVAR) χρησιμοποιώντας τέσσερις μεταβλητές: παγκόσμια προσφορά πετρελαίου, παγκόσμια ζήτηση πετρελαίου, basis των συμβολαίων μελλοντικής εκπλήρωσης επί του αργού πετρελαίου και γεωπολιτικός κίνδυνος.

Τα κύρια αποτελέσματα της μελέτης δείχνουν ότι to basis των συμβολαίων μελλοντικής εκπλήρωσης αργού πετρελαίου έχει σημαντική θετική απόκριση στον αυξημένο γεωπολιτικό κίνδυνο. Ωστόσο, δεν διαπιστώθηκε άμεση επίδραση του γεωπολιτικού κινδύνου στην προσφορά και τη ζήτηση πετρελαίου. Τα αποτελέσματα υποδηλώνουν ότι η οικονομική και πολιτική αβεβαιότητα επηρεάζουν τις προσδοκίες για μελλοντικές αλλαγές στη διαθεσιμότητα πετρελαίου. Μπορεί να υποστηριχθεί ότι οι συμμετέχοντες στην αγορά αναμένουν διαταραχή της προσφοράς πετρελαίου ως αποτέλεσμα εξελίξεων που διαταράσσουν τη γεωπολιτική σταθερότητα.

Table of Contents

List of Figures

List of Tables

1. Introduction

Oil is regarded as one of the most important types of commodities, mainly because of the multitude of ways it can be used, turning into plastic, asphalt, and fuel. The oil industry plays a vital role in the energy market and greatly influences the global economy as one of the world's primary fuel sources. That is why oil prices are closely watched by a wide range of market participants like corporations, investors, traders, and governments.

Over the last years, a significant part of the literature has focused on the key factors that determine crude oil prices and the relationship between oil and the global economy in general. However, there are sometimes conflicting views and, at the same time, an overall lack of research regarding the impact of geopolitical risk on oil prices during the COVID-19 pandemic.

Several studies have identified a significant relationship between geopolitical risk and crude oil (see Antonakakis et al., 2017b), while there has been research suggesting the opposite view (see Noguera-Santaella, 2016). However, these studies were conducted before the year 2019 without taking into consideration – or even imaging at the time - the extreme events that took place due to the COVID-19 pandemic that disrupted the global economy. As a result, it is not clear whether the results presented are still relevant after the outbreak of the pandemic.

This research aims to add to the existing literature by studying the impact of geopolitical risk on oil futures using a structural vector autoregressive (SVAR) model, following the approach of Kilian (2009), Kilian and Park (2009), and Chen et al. (2016). More recent data will be included in the sample to capture the effects of COVID-19 on the relationship between oil prices and geopolitical risk. The main focus will be to examine how this relationship has developed in more recent years – in light of the events happening at this time between Ukraine and Russia – and whether the COVID-19 pandemic has caused significant disruptions by answering the two following research questions. First, has the relationship between oil prices and GPR changed over time due to more recent events of acts and threats? Second, how is the oil market responding to geopolitical risk, taking into consideration the impact of COVID-19?

The study will contribute to the ongoing research regarding the impacts of the COVID-19 pandemic on the global economic and social life. By using more recent data and capturing the effects of recent events on the relationship between oil prices and geopolitical risk, it will be clear whether or not the relationship has changed over time. The importance of GPR has been highlighted by Huang et al. (2021), as it contains effective information about oil price volatility. Such information is essential for investors to help optimize their portfolios and for risk managers to effectively cushion the effects of GPR.

The rest of the thesis is organized as follows. In Chapter 2, the existing literature will be reviewed to identify key findings regarding the relationship between oil prices, geopolitical risk, and the global economy. In Chapter 3, the data will be described. In Chapter 4, the theoretical framework will be outlined, together with a range of tests that need to be done for the model to be accurate and provide significant results. In Chapter 5, the empirical results are presented and further discussed. Finally, Chapter 6 concludes.

2. Literature Review

2.1. Crude oil and the global economy

Over the last years, a significant part of the literature has focused on the key factors that determine crude oil prices and the relationship between oil and the economy in general. Bernanke et al. (1997) studied the response of oil price shocks to endogenous monetary policy using an identified VAR model and found that a significant part of the effect of oil price shocks on the economy can be attributed to the resulting tightening of monetary policy and not the change in oil prices itself. At the same time, the relationship between oil prices and the stock market has also been extensively studied. Kling (1985) concludes that in some industries stock prices are affected by crude oil prices with a lag, whereas Chen et al. (1986) and Wei (2003) suggest that there is a limited effect of oil price changes on stock prices. A more recent study by Kilian and Park (2009) strengthens the argument of a significant relationship between oil and the stock market but differentiates between the effect of oil price shocks caused by the production of crude oil or aggregate demand. Furthermore, other studies have identified the connectedness between oil and other energy commodities. For example, Bencivenga et al. (2010) and Frydenberg et al. (2014) report a long-term relationship between oil, electricity, and natural gas using cointegration tests. Naeem et al. (2020) found a strong link between oil price shocks and clean energy by examining the relationship among oil demand and supply shocks, major energy commodities, and clean energy futures.

2.2. Research on crude oil futures

It is a common practice in policy institutions to use the price of NYMEX oil futures as a proxy for the market's expectation of the spot price of crude oil (Alquist and Kilian, 2010). Examining the oil futures spread and the determinants of oil futures prices can provide significant policy implications. Although Alquist and Kilian (2010) conclude that oil futures prices are not the best available predictor of future oil prices, the study of this topic remains relevant since oil futures can affect policy-making decisions and may be a useful hedge for investors. Kang et al. (2020) suggest that crude oil futures price volatility is responsive to macroeconomic conditions and financials such as industrial production, credit spreads, US dollar index, and interest rates. Dempster et al. (2012) perform a structural vector auto-regression (SVAR) analysis and find that the business cycle and fundamental variables, as also financial and trading variables, affect the movement and the shape of the oil futures price term structure.

2.3. The relationship between crude oil and geopolitical risk

Oil is a global industry and events worldwide can have a small or even significant impact on the price of oil, especially since the production of oil mainly happens in areas where the political conditions can be quite unstable. Most crude oil reserves in the world are in regions that have been prone to political upheaval or in regions that have had oil production disruptions because of political events. Political events have produced supply disruptions and big oil price shocks at the same time. These include the Arab Oil Embargo in 1973–74, the Iranian Revolution, the Iran–Iraq War in the 1980s, and the Persian Gulf War in 1990–91. Conflicts and political events in the Middle East, the Persian Gulf, Libya, and Venezuela in recent years have contributed to disruptions in the world's oil supply and rises in oil prices. (EIA, 2022).

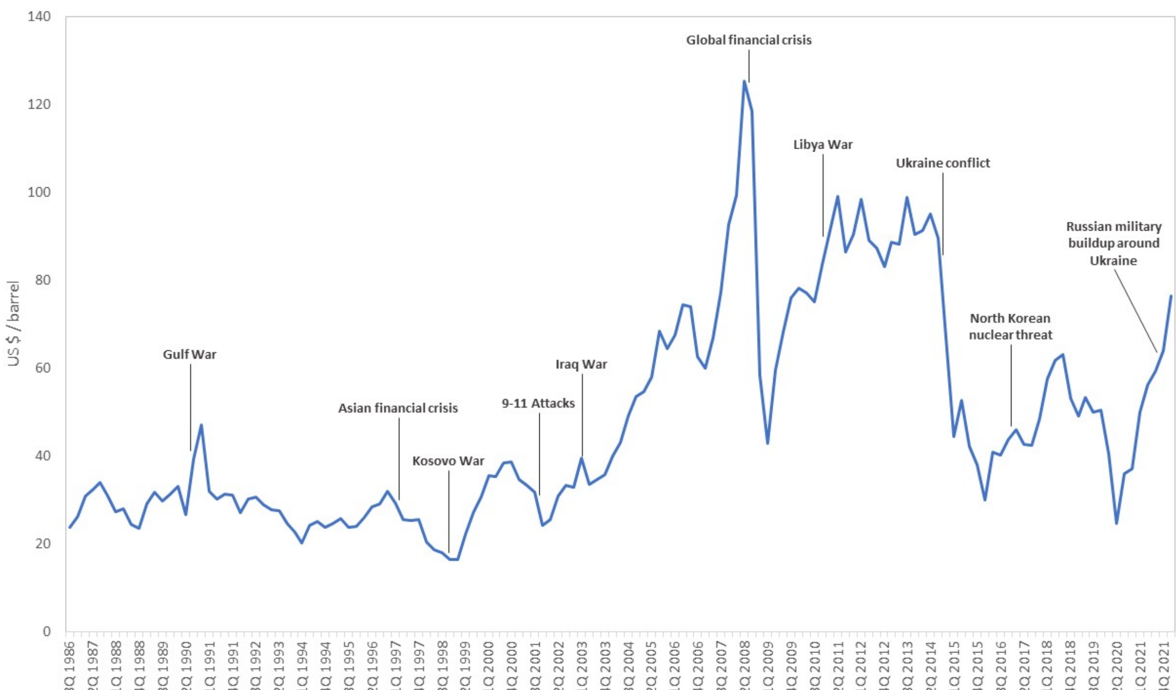

Figure 1: Crude oil prices and key geopolitical and economic events
Source: US Energy Information Agency (2022)

Entrepreneurs, market participants, and central bank officials view geopolitical risks as key determinants of investment decisions and stock market dynamics (Caldara and Iacoviello, 2022). Therefore, we must add geopolitical risk as a predictor of oil price movements, besides macroeconomic and financial factors. The effects of geopolitical risks on financial and macroeconomic variables have not been the subject of many empirical investigations. The most notable limitation has been the lack of an indicator of geopolitical risk that can measure risk in real-time and is consistent over time. (Bouoiyou et al., 2019).

However, in recent years there is a large volume of literature that emphasizes the importance of geopolitics in analyzing oil price dynamics. Increased geopolitical risk in certain areas of the world can have either a negative impact on oil prices, when economic activity is reduced and oil demand decreases (see Caldara and Iacoviello, 2022; Cunado et al., 2020) or a positive effect on prices if the principal impact of higher geopolitical risk is on the supply side (see Bouoiyou et al., 2019; Smales, 2021). Furthermore, the relationship between geopolitical risk and oil price volatility has been extensively studied and the findings imply that geopolitical tensions can significantly affect oil price volatility (Antonakakis et al., 2017b; Liu et al., 2019; Wang et al., 2020; Qin et al., 2020; Smales, 2021). On the other hand, Noguera-Santaella (2016) finds that geopolitical events affected the volatility of oil prices for the period until 2000, but they have not been so important after that date.

Considering oil is strongly connected with the stock market, the relationship between these two markets has been also studied during periods of geopolitical unrest. Antonakakis et al. (2017a) find that different oil price shocks transmit different shocks to the stock market over different periods and Kollias et al. (2013) mention that the oil price–stock market relationship is affected in the event of a war, while in the case of one-off security shocks such as terrorist attacks that they examined the relationship of stock indices with oil can either be affected (CAC, DAX) or remain intact (S&P500, FTSE5100).

A very interesting part of the research has been the bidirectional relationship between geopolitical risk and oil volatility. Huang et al. (2021) constructed a DCC-MVGARCH model based on high-frequency data to test causality between GPR and oil prices by using nonlinear Granger causality tests. They conclude that large changes in oil price volatility can result in changes in the current level of geopolitical risk through economic activities since oil price is a leading economic indicator. On the other hand, they observed that GPR mainly affects oil volatility rather than oil returns and this effect is visible after the crisis. Ivanovski and Heilemariam (2022) add to the research on the drivers of geopolitical risk by examining a data range from 1997 to the beginning of 2020 and find that oil price and oil volatility have a time-varying effect on geopolitical risk. Specifically, their study suggests that oil price is negatively associated with geopolitical risk for much of the sample period used, but the effect is declining in recent periods. Furthermore, increased oil price volatility results in higher geopolitical risk.

2.4. Recent findings on the COVID-19 period

Crude oil futures have been severely impacted by COVID-19. A sharp decrease in demand for crude oil combined with a volatility of investor sentiment resulted in a negative WTI crude oil futures price on April 20, 2020. Further studying the impact of COVID-19, Huang and Zheng (2020) examined the long-run relationship between investor sentiment and the WTI oil futures price index and found a structural change due to COVID-19. One implication of this finding is that COVID-19 will need to be specifically modeled. By examining the period 2019-2021, divided into three sub-periods (pre-COVID-19 period, pre-vaccine period, and post-vaccine period), Katsampoxakis et al. (2022) investigated the impact of the pandemic on the relationship between oil and stock indices. Their study suggests that because of COVID-19 the interdependence between crude oil and the stock market for both oil-importing and oil-exporting countries is increasing in the short term, although long-run equilibrium for the variables does not exist. Regarding oil prices and geopolitical risk, a limited number of studies have been conducted in recent years to explore this relationship under the prism of the COVID-19 outbreak. The main limitation has been the small size of the sample given the short period that can be investigated. In this area, Sharif et al. (2020) suggest that the COVID-19 pandemic itself and related regulatory response to this crisis are sources of geopolitical risk and recommend including the geopolitical risk index in the future analyses of the financial effects of the COVID-19 outbreak.

3. Data

3.1. Global crude oil production

The global crude oil production is used as a measure of global oil supply. Monthly data are available in the Monthly Energy Review of the Energy Information Administration (EIA). Global production is measured in thousand barrels per day. For the model applied in this study, the percentage change in global crude oil production is used (PROD).

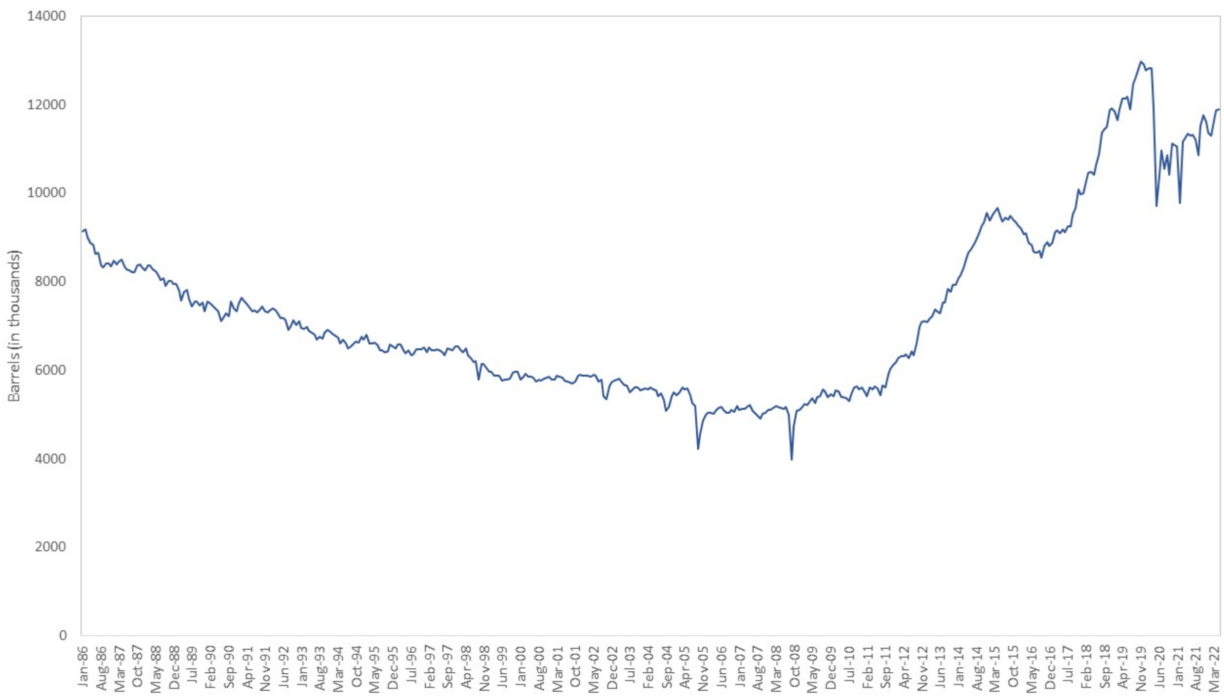

Figure 2: Global oil production in thousand barrels

3.2. Global real economic activity

As a proxy for global oil demand, the global real economic activity index[1] (GREA) will be used in this study. The index was initially developed in Kilian (2009) and recently an updated version was introduced which included some corrections to the initial index (see Kilian, 2019). The index is based on dry cargo single voyage ocean freight rates and captures changes in the demand for industrial commodities in global business markets.

[1] The index can be found at: https://www.dallasfed.org/research/igrea.aspx

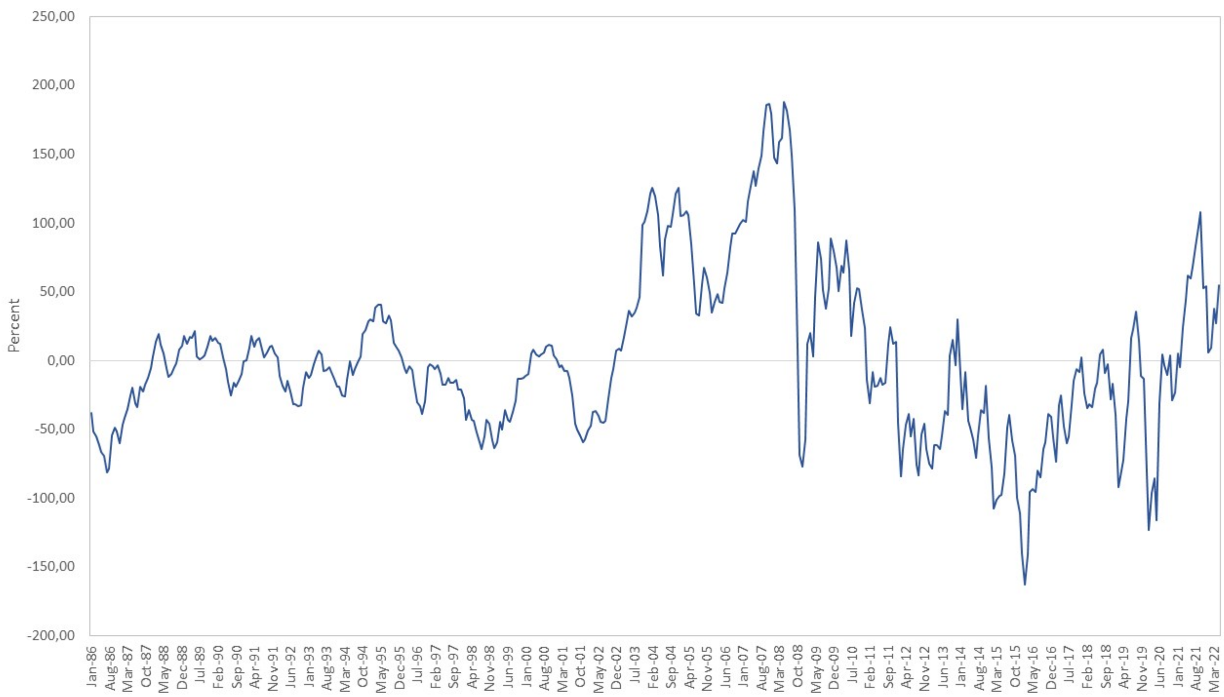

Figure 3: Monthly index of Global Real Economic Activity

3.3. Crude oil futures

The West Texas Intermediate (WTI) is typically used as the benchmark for pricing the most widely traded oil-based derivatives worldwide, therefore for this work the WTI oil futures basis (BASIS) will be used. The data range from January 1986 to May 2022 and were obtained by the Energy Information Administration (EIA) database[2]. The Basis is calculated as follows:

$$\text{Basis} = \text{WTI Spot Price} - \text{3-month crude oil futures price}$$

[2] The monthly WTI oil futures prices can be found at: https://www.eia.gov/dnav/pet/pet_pri_fut_s1_m.htm and monthly Spot Prices at: https://www.eia.gov/dnav/pet/pet_pri_spt_s1_m.htm .

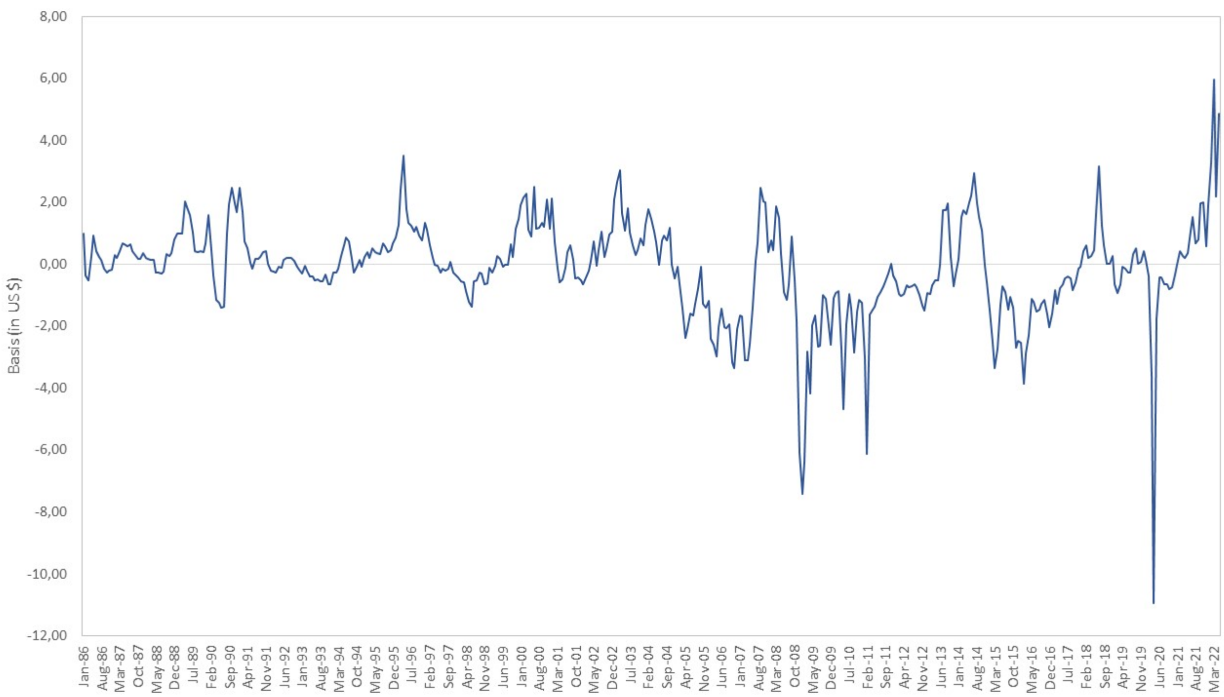

Figure 4: NYMEX West Texas Intermediate (WTI) 3-month Crude Oil futures basis

3.4. Geopolitical risk

Following previous work, the geopolitical risk (GPR) index of Caldara and Iacoviello is used here as the measure of geopolitical risk. The GPR index is constructed by counting, each month, the share of articles discussing adverse geopolitical events and associated threats. The articles are published in leading newspapers in the United States, the United Kingdom, and Canada and cover geopolitical events of global interest (Caldara and Iacoviello, 2022).

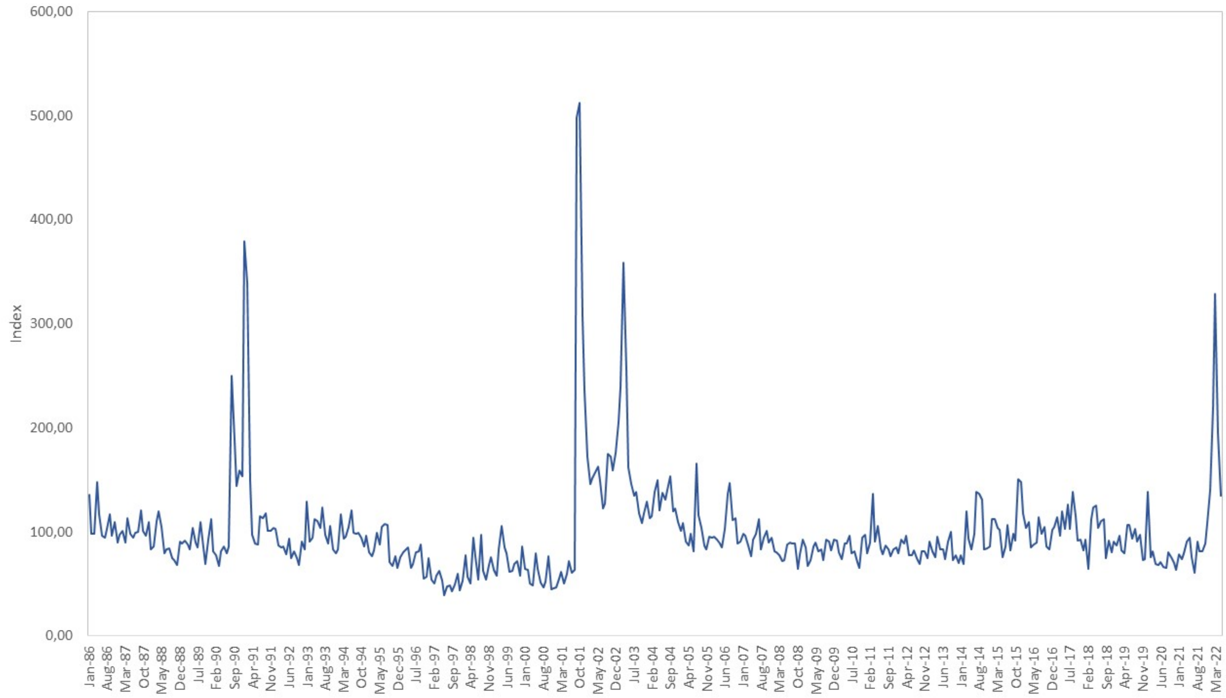

Figure 5: Monthly index of Geopolitical Risk

4. Methodology

In this study, the relationship between geopolitical risk and crude oil futures will be investigated using a Structural Vector Autoregressive Model (SVAR). As mentioned above, four variables will be included in the model: global crude oil production, the global real economic activity index, crude oil futures basis, and the geopolitical risk (GPR) index. A variety of tests and methods are employed, such as unit root tests, cointegration, Granger-causality, and impulses analysis. First, unit root tests are conducted to test for stationarity of the time series, since this property is necessary for the other techniques. In case the variables are non-stationary, the cointegration test is used to measure the long-run relationship between two or more time series, while the short-term relationship can be described by the Granger-causality test, and impulses analysis. A group of variables may not be stationary, but if cointegration is found, it signifies that over the long term, they never drift apart. On the other hand, if no cointegration can be found, there is no long-run relationship. Also, in the case of cointegrating variables, the Granger-causality test, and impulses analysis must be constructed using an error correction model. When there is no cointegration for non-stationary variables, all the analyses can be based on a standard VAR model in first differences. The Granger-causality test is used to determine the causal relationship between the variables, and the impulses analysis looks at the frequency and length of their interactions.

4.1. Unit root and stationarity tests

It is very common in econometric research for time series to exhibit non-stationary behavior. In those cases where a simple regression is used to estimate the relationship between non-stationary variables, we may have to deal with the problem of spurious regression. (Granger and Newbold, 1974). In spurious regressions, there is misleading evidence of a relationship between independent values, because the correlation coefficient R^2 is visibly increased. A very common practice to counter this problem is usually using the first differences of the time series in the analysis. Many approaches are available to examine the stationarity of time series data. The most commonly used in the literature are the Augmented Dickey-Fuller (ADF) test, Phillips-Perron test (PP), Kwiatkowski, Phillips, Schmidt, and Shin (KPSS, 1992) test. For the purposes of this thesis, the ADF test and KPSS test will be used.

4.1.1. Unit Root Test - Augmented Dickey-Fuller (ADF) test

The Augmented Dickey-Fuller (ADF) test was developed by Dickey and Fuller and can be used to test for unit roots in higher-order autoregressive processes besides autoregressive first-order models AR (1). There are three main versions:

i. Test for a unit root

$$\Delta y_t = \phi^* y_{t-1} + \sum_{i=1}^{p-1} \phi_i \Delta y_{t-i} + u_t$$

ii. Test for a unit root with drift

$$\Delta y_t = \beta_0 + \phi^* y_{t-1} + \sum_{i=1}^{p-1} \phi_i \Delta y_{t-i} + u_t$$

iii. Test for a unit root with drift and deterministic time trend

$$\Delta y_t = \beta_0 + \phi^* y_{t-1} + \sum_{i=1}^{p-1} \phi_i \Delta y_{t-i} + \beta_1 t + u_t$$

Where y_t denotes the variable at time t and $\Delta y_t = y_t - y_{t-1}$. β_0 is the drift term, t is a linear trend term and u_t is the error term. The hypotheses of the test are the following:

$$H_0: \phi^* = 0 \quad Non-stationary$$

$$H_1: \phi^* < 0 \quad Stationary$$

The null hypothesis is that the process is non-stationary, i.e. the time series contains a unit root, whereas the alternative is that the process is stationary. The T-statistic $\tau = \frac{\varphi^*}{\sqrt{var(\varphi^*)}}$ must be calculated and compared to the appropriate critical value at various levels of significance to determine whether a unit root exists. It is determined that a series y_t does not contain a unit root if the null hypothesis is rejected.

In order to run the Augmented Dickey-Fuller (ADF) test, it must be specified first if a constant or a constant and a linear trend should be included in the test regression. One strategy is to rely on a series' graphical examination (Verbeek, 2017). We can determine whether there is an obvious trend, if the data starts at the origin, or if a constant is required by looking at the data plot.

The power of the test is low if the process is stationary, but there is a root that is close to the non-stationary boundary, which is the most significant critique of the Augmented Dickey-Fuller (ADF) test (Brooks, 2008).

4.1.2. Stationary Test - Kwiatkowski, Phillips, Schmidt, and Shin (KPSS) test

Kwiatkowski, Phillips, Schmidt, and Shin (1992) proposed an alternative test in which the null hypothesis assumes the stationarity of y_t, in order to get around this constraint of the Augmented Dickey-Fuller (ADF). The test statistic for the KPSS test, which is a Lagrange multiplier test, is obtained by regressing the dependent variable y_t on a constant or a constant and a time trend t. Then the OLS residuals ε_t are saved and the partial sums $S_t = \sum_{t=1}^{T} \varepsilon_S$ are computed for all t. The test statistic is mentioned in Verbeek (2017) as:

$$\text{KPSS LM} = \sum_{t=1}^{T} \frac{S_t^2}{\hat{\sigma}_\varepsilon^2}$$

Where $S_t = \sum_{t=1}^{T} \varepsilon_S$ and $\hat{\sigma}_\varepsilon^2$ is the variance of estimated error from the following regression:

$$y_t = \alpha + \epsilon_t \quad \boldsymbol{or} \quad y_t = \alpha + \beta t + \epsilon_t$$

It is common for both methods to be used to test stationarity, so that the conclusion is robust. This way the results can be compared to see if the same conclusion is obtained.

4.2. Vector autoregressive (VAR) models

Vector autoregressive (VAR) models, first introduced by Sims (1980), can be used to depict the dynamics and interdependency of multivariate time series. It is viewed as a generalization of univariate autoregressive models or as a combination of simultaneous equations models and univariate time series models.

The basic VAR(p) process can be written as:

$$y_t = A_1 y_{t-1} + \cdots + A_p y_{t-p} + u_t$$

where $\boldsymbol{y_t}$ is a (K x 1) random vector, the A_i are fixed (K x K) coefficient matrices and u_t is a K-dimensional white noise term with $\mathrm{E}\,(\mathrm{u_t}) = 0$ and $\mathrm{E}\,(\mathrm{u_t u_s'}) = 0$ for $\mathrm{s} \neq \mathrm{t}$.

VAR models provide in general more flexibility because there is no need to specify which variables are endogenous and which are exogenous. For a variable to be included in a VAR model, stationarity is necessary. If the variables are non-stationary, their first differences are tested for cointegration. In the case of cointegrated time-series, a Vector Error Correction Model (VECM) is used instead of a VAR model, which releases the stationarity requirement of the data. Otherwise, a VAR model in first differences can be estimated.

Regarding the optimal lag length that will be selected to estimate the VAR (p) model, there are different criteria used in the literature. The most common are the following:

- Akaike Information Criterion (AIC)
- Bayesian Information Criterion (BIC)
- Hannan-Quinn Information Criterion (HQ)
- Likelihood Ratio (LR) Test

The Akaike Information Criterion (AIC) is found on information theory. Information transmission, processing, extraction, and usage are all covered under the field of applied mathematics known as information theory. For a certain data set, it employs AIC to assess the relative merits of economic models.

Model selection from a limited number of models is done using the Bayesian information criterion (BIC), also known as Schwarz Criterion. Models with lower BIC are typically favoured in general. It shares several similarities with the previously discussed Akaike information criterion (AIC) and is partially based on the likelihood function.

Another selection criterion for models is the Hannan-Quinn information criterion (HQC). It is occasionally used in place of the AIC and BIC. Contrary to AIC, the BIC and the Hannan-Quinn information criteria are not asymptotically efficient.

Finally, the Likelihood-Ratio test evaluates the goodness of fit of two competing statistical models by comparing their likelihoods, specifically one derived via maximizing over the entire parameter space and another found after imposing some limit. The likelihood-ratio test demands that the models be nested, meaning that the more complex model can be made into the simpler model by placing restrictions on the parameters of the former.

4.3. Cointegration in Time-Series

Cointegration in time series refers to the case when two or more variables have a long-run relationship. This means, that a long-term equilibrium can be found for the variables, but not one in the short-term.

According to Engle and Granger (1987), two time series Y_t and X_t are said to be cointegrated of order (d,b) where $0 \leq b \leq d$ if both time series are integrated of order d and there is a linear combination of these two time-series, $\alpha_1 Y_t + \alpha_2 X_t$ which is integrated of order (d-b).

If

$$Y_t \sim I(d) \text{ and } X_t \sim I(d) \text{ then } Y_t, X_t \sim CI \text{ if } \alpha_1 Y_t + \alpha_2 X_t \sim I(d-b)$$

where the symbol CI is used to indicate cointegration. The vector $[\alpha_1, \alpha_2]$ is called the cointegration vector. If the variables are stationary, i.e., integrated of order 0, we can proceed to standard regression techniques.

4.3.1. The Engle-Granger Method

This cointegration control method was introduced by Engle and Granger (1987). The following steps must be followed to perform the test:

1. The order of integration of the variables Y_t and X_t is investigated with the methodology of unit roots. If the order of integration is the same for both variables, we can proceed to the next step. If they are not of the same order, there is no cointegration.
2. If the variables are of the same order, the long-term equilibrium relationship can be estimated by using the least squares method (OLS).

$$Y_t = a_0 + a_1 X_t + e_t$$

, where e_t are the long-term equilibrium errors.

For the two variables to be cointegrated, the regression errors must be stationary. Therefore, we apply the Dickey-Fuller (DF) stationarity test or the Augmented Dickey-Fuller (ADF) test, after first estimating the following equation with OLS:

$$\Delta e_t = \gamma e_{t-1} + \sum_{j=1}^{\rho-1} (\Delta e_t - j) + ut$$

The following two hypotheses are assumed to conclude about the cointegration of the variables:

H_0: γ=0, no stationarity in the residuals

H_1: γ<0, stationarity in the residuals

The null hypothesis of non-stationarity is rejected when $t < \tau_\gamma$, where τ is the critical value of the table presented by Engle and Granger for checking the stationarity of errors.

4.3.2. The Johansen method

The Johansen method is a process of testing the cointegration in time series (Johansen, 1988) and is one of the most common testing methods in the literature. In contrast to the method proposed by Engle and Granger, this method is based on the vector autoregressive model (VAR). A VAR model is used to describe a set of variables measured over a period as a linear function of their lags. In most VAR models symmetric lags are applied, i.e., every variable in the model has the same lag. The Johansen method helps to find the maximum number of cointegration relationships based. Multiple equations can be tested simultaneously, while the Engle-Granger method can test only one equation at a time. The method starts with the following VAR model:

$$y_t = A_1 y_{t-1} + A_2 y_{t-2} + \cdots + A_p y_{t-p} + e_t$$

where $\boldsymbol{y_t}$ is a (n x 1) matrix and $\mathbf{A}$ is a (n x n) matrix. The above equation can also be expressed as:

$$\Delta y_t = \Pi y_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta y_{t-1} + e_t$$

where $\Pi = (\sum_{i=1}^{p} A_i) - I$ and $\Gamma_i = -\sum_{j=t+1}^{p} A_j$.

If the coefficient matrix Π has reduced rank $r<n$, then the (n x r) matrices α and β exist and each has rank r such that $\Pi = \alpha\beta'$ and $\beta y_t'$ is stationary. The order r of matrix Π determines the number of cointegrating relationships, the elements of α are known as the adjustment parameters in the vector error correction model and each column of β is a cointegrating vector. So, if $r = 0$, there are no cointegration relationships. If r is equal to the number of variables, then they are stationary, and if $r < n$, then the variables are cointegrated.

Johansen (1988) proposed two statistics to find the order of matrix Π, the trace test and the maximum eigenvalue test.

4.3.2.1. Trace Test

The trace test examines the null hypothesis of the existence of r cointegration vectors, and the alternative hypothesis is that there may be more cointegration vectors than the necessary number of nulls.

$$H_0: r = 0$$

$$H_1: r \geq 1$$

Testing if $\lambda_{\text{trace}}(r)$ > critical value. Continuing with the next test:

$$H_0: r \leq 1$$

$$H_1: r \geq 2$$

Testing again the value of $\lambda_{\text{trace}}(r)$ until a non-statistically significant result is found. The number of the relevant null hypothesis is also the order of the table.

$$\lambda_{\text{trace}}(r) = -T\sum_{i=r+1}^{g} \ln(1 - \hat{\lambda}_i) \text{ , where: } j = r+1,\ldots,n \text{ kai } r = 0,1,2,3,\ldots, n-1$$

4.3.2.2. Maximal Eigenvalue Test

In this scenario, the alternative claims that there are r+1 vectors, while the null hypothesis is that the number of vectors is equal to r.H_0: r = 0

$$H_1: r = 1$$

Testing if λ_{max} > critical value. Continuing with the next test:

$$H_0: r \leq 1$$

$$H_1: r = 2$$

testing again the value of λ_{max} until a non-statistically significant result is obtained. The table's order is determined by the number of the pertinent null hypothesis.

$$\lambda_{max}(r,r+1) = -Tlog(1-\lambda_{r+1})$$

4.4. Granger Causality

An apparent association between two variables can be estimated using a simple regression, as was already explained. However, a statistically significant estimator does not necessarily imply a causal connection. Granger causality, a statistical hypothesis test for detecting whether one time series is useful in forecasting another, was created as a result (Granger, 1969).

In time series, it is interesting to investigate causality, i.e., if there is a two-way, one-way, or no causal relationship between the causes of the changes in one variable and the changes in the other variables.

Assume that there are two time series, X_t and Y_t. When the lagged and present values of Y_t provides some helpful information for predicting X_{t+1} at time t, it is said that Y_t causes X_t by Granger.

4.4.1. Granger Causality Test

The Granger Causality test, which Granger devised, is the technique that has become the de facto standard for determining whether two variables are causally related. Let's assume once more that there are two stationary time series, X_t and Y_t, which are as follows:

$$Y_t = \sum_{i=1}^{m} \alpha_i Y_{t-i} + \sum_{i=1}^{m} \beta_i X_{t-i} + u_t$$

$$X_t = \sum_{i=1}^{m} \gamma_i X_{t-i} + \sum_{i=1}^{m} \delta_i Y_{t-i} + e_t$$

where m is the number of lags according to model order selection method.

These two equations contain the following two causal relationships: In the first relationship, the value of Y at time t depends on both the time lag value of X and the time lag value of $Y(Y_{t-i})$. The value of X at time t in the second equation depends not only on its time lag value (X_{t-i}), but also on the time lag value of Y. The statistical significance of the coefficients β_i and δ_i in both equations will be determined in this instance with the use of the statistic F in order to ascertain whether there is a causal relationship between the two variables. The F statistic is calculated using:

$$F = \frac{\frac{SSR^R - SSR^{UR}}{m}}{\frac{SSR^{UR}}{n-k}}$$

- SSR^R and SSR^{UR} are the sums of squares due to regression for the restricted/reduced model and the unrestricted/full model respectively.

- n is the sample size (where m<n)
- k is the number of parameters without restriction (n-k degrees of freedom)

The existence of causality and its direction will be determined after testing both equations, and there are four possible outcomes.

- **Outcome 1:** The coefficient β_i is statistically significant ($\beta_i \neq 0$), but the coefficient δ_i is not ($\delta_i = 0$). According to Granger there a one-way causality from X to Y, meaning that lagged values of X help predict Y.
- **Outcome 2:** The coefficient δ_i is statistically significant ($\delta_i \neq 0$), but the coefficient β_i is not ($\beta_i = 0$). According to Granger there a one-way causality from Y to X, meaning that lagged values of Y help predict X.
- **Outcome 3:** The coefficients β_i and δ_i are both statistically significant (β_i, $\delta_i \neq 0$) so there is a Granger two-way causality between the variables. Each coefficient's lagged values help in the prediction of the other.
- **Outcome 4:** The coefficients β_i and δ_i are not statistically significant ($\beta_i = 0$, $\delta_i = 0$) and no Granger causality relationship between the two variables exists.

4.5. Impulse response functions

The term "impulse response" refers to the reaction of a dynamic system in response to some external changes. Impulse responses, in particular, focus on how the dependent variables respond to shocks from each independent variable in VAR systems (Lütkepohl, 2005). Standard deviations are frequently used to express the shocks. In light of this, the impulse response function summarizes the effects of changing disruptive situations on endogenous variables over a number of future periods. To put it another way, one can examine how one variable reacts to an unforeseen shock by using impulse response functions. An unanticipated shock to one variable is transmitted to the other endogenous variables of the system, because of the dynamic structure of the VAR model. However, Lütkepohl and Reimers (1992) stated that the traditional impulse response analysis requires orthogonalization of shocks. Additionally, the outcomes differ depending on the VAR's variable ordering. The significance of the variable ordering increases with the residual correlations. Generalized impulse response functions were created by Pesaran and Shin (1998) to address this issue by adjusting the impact of different variable orderings on impulse response functions. The generalized impulse responses are represented graphically using historical correlation trends.

4.6. The structural VAR model

As described above, impulse responses are an essential tool for revealing the relationships between the variables in a VAR model, but there are some challenges in interpreting them. Particularly, impulse reactions are typically not singular, and it is frequently unclear which set of impulse reactions best captures the dynamics of a given system. The proper set for a given model must be chosen using non-sample information because the various sets of impulses can all be calculated from the same underlying VAR. To identify the pertinent innovations and impulse responses, structural restrictions are needed when using VARs, which are reduced form models in econometrics (Lütkepohl, 2005). In this case, an alternative structural vector autoregressive (SVAR) model can be considered.

The general modeling strategy for SVARs is to specify and estimate a reduced form model first and then focus on the structural parameters and the resulting structural impulse responses.

4.6.1. Estimating the SVAR model

A SVAR is the structural form of VAR. Based on the VAR equation, a SVAR representation is:

$$\mathbf{A}y_t = A_1^* y_{t-1} + \cdots + A_p^* y_{t-p} + \mathbf{B}\epsilon_t$$

where $A_j^* = \mathbf{A}A_j$ (j=1, …, p) and $\epsilon_t = \mathbf{B}^{-1}\mathbf{A}u_t$. The correlated components of the VAR residuals u_t will be transformed into uncorrelated structural residuals ϵ_t, which will have a diagonal covariance matrix $\sum_\epsilon$ with proper choice of **A** and **B**.

For this thesis, we first define the following vector $\boldsymbol{y_t}$ to analyze the relationship between geopolitical risk and oil futures price movements:

$$\boldsymbol{y_t} = [GPR_t, \quad PROD_t, \quad GREA_t, \quad BASIS_t]$$

Then, a SVAR model is established using the vector $\boldsymbol{y_t}$:

$$A_0 y_t = \alpha + \sum_{i=1}^{p} A_i \mathrm{y}_{\mathrm{t-i}} + \epsilon_t$$

In the above equation, p is the lag-length of the SVAR model and is determined by the Akaike Information Criterion (AIC) and ϵ_{t} denotes the vector of serially and mutually uncorrelated structural innovations. Assuming matrix A_0 has a recursive structure, let u_t denote the innovations of the reduced VAR model such that $u_t = A_0^{-1}\, \epsilon_{\mathrm{t}}$. By placing exclusion restrictions on A_0^{-1}, it is possible to extract the structural innovations from the reduced-form innovations. The errors u_t can be decomposed into the following components:

$$\boldsymbol{u_t} = \begin{bmatrix} u_t^{GPR} \\ u_t^{PROD} \\ u_t^{GREA} \\ u_t^{BASIS} \end{bmatrix} = \begin{bmatrix} \alpha_{11} & 0 & 0 & 0 \\ \alpha_{21} & \alpha_{22} & 0 & 0 \\ \alpha_{31} & \alpha_{32} & \alpha_{33} & 0 \\ \alpha_{41} & \alpha_{42} & \alpha_{43} & \alpha_{44} \end{bmatrix} \begin{bmatrix} \epsilon_t^{Geopolitical\ risk\ shock} \\ \epsilon_t^{Supply\ shock} \\ \epsilon_t^{Demand\ shock} \\ \epsilon_t^{Oil\ price\ shock} \end{bmatrix}$$

where element 0 in the matrix indicates that no expected contemporaneous responses to a given shock exist.

5. Empirical results

5.1. Descriptive statistics

First, some descriptive statistics for the variables used are presented and a summary is given in the table below. The Geopolitical Risk Index (GPR) took a very high maximum value, around the time that the 9/11 events occurred, compared to relatively low Average and Median values. The percentage change in global crude oil production (PROD) has a very small positive average value, mainly impacted by the great increase in production after the year 2012. The global real economic activity index (GREA) has an average value close to 0, but high volatility, as expressed by the standard deviation. The crude oil futures basis (BASIS) has a small negative average value, which can be interpreted as the oil market being in contango on average. Finally, all variables except for GREA seem to have high Kurtosis values, which implies the existence of outliers in the data set. This is also visible from the charts presented in Chapter 3.

	GPR	PROD	GREA	BASIS
Mean	99.88742	0.103189	0.606776	-0.144737
Median	89.79545	0.007765	-6.437351	-0.050000
Maximum	512.5297	19.22956	188.1794	5.980000
Minimum	39.04562	-20.57555	-163.0020	-10.93000
Std. Dev.	48.84170	2.797713	58.89133	1.556318
Skewness	4.410870	-1.246115	0.755877	-1.277434
Kurtosis	30.53898	24.71938	3.892264	10.41132
Observations	437	437	437	437

Table 1: Descriptive statistics of data set

5.2. Unit root and stationarity tests

From the graphical representation of the variables, it is difficult to assert whether the time series are stationary or non-stationary. As a result, the stationary qualities of the time series are investigated using the Augmented Dickey-Fuller (ADF) test and the Kwiatkowski, Phillips, Schmidt, and Shin (KPSS) test. The ADF test's null hypothesis implies the existence of a unit root, which denotes the time series' non-stationarity. In order to acknowledge the stationarity of the time series, the null hypothesis must be rejected. On the other hand, the null hypothesis of the KPSS test is that the time series is stationary and will be used complementary to the ADF test.

In Table 2 the results of the ADF test are presented separately for each time series. In every case, the value of the t-statistic is negative and lower than the critical value at a significance level of 5%. Since the p-value is lower than 0.05 and close to 0 in most cases, we reject the null hypothesis. Thus, we conclude that all variables are stationary.

Augmented Dickey-Fuller (ADF) test		
Variables	**t-statistic**	**p-value**
GPR	-6.817901	0.0000
PROD	-17.77830	0.0000
GREA	-4.039095	0.0014
BASIS	-6.585770	0.0000

Critical value for ADF test at 5% level = -2.867965

Table 2: Results of Augmented Dickey-Fuller test

Additional to the ADF test, we obtain similar results while performing a KPSS test for the stationarity of the time series. In Table 3 we obtain the results from the KPSS test. In every case, the value of the LM-statistic is lower than the critical value at a significance level of 5%, so we confirm the stationarity of the time series.

KPSS test	
Variables	**LM-statistic**
GPR	0.064768
PROD	0.054671
GREA	0.094182
BASIS	0.120103

Critical value for KPSS test at 5% level = 0.146000

Table 3: Results of the KPSS test

Since all variables are stationary, i.e. I(0), they are included in levels in the SVAR model. Furthermore, there is no need to conduct a cointegration test between the variables, because a test for cointegration is only necessary in the case of I(1) variables.

5.3. Lag length selection

Before estimating the reduced form VAR model, the optimal number of lags should be decided first. The Akaike Information Criterion (AIC) and the Likelihood Ratio Test are used for this purpose. As we can see in Table 4, both methods suggest that the appropriate number of lags is 5. The other two commonly used criteria, Schwarz Criterion and Hannan-Quinn information criterion, suggest 1 and 2 lags respectively. These results are rejected, because of concerns regarding autocorrelation, as will be discussed later.

VAR Lag Order Selection Criteria

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-6474.285	NA	1.54e+08	30.20179	30.23966	30.21675
1	-5566.915	1793.588	2408996.	26.04622	26.23557*	26.12100
2	-5529.707	72.85593	2182249.	25.94735	26.28817	26.08194*
3	-5508.267	41.57926	2127713.	25.92199	26.41429	26.11640
4	-5494.953	25.57273	2154722.	25.93451	26.57829	26.18875
5	-5469.695	**48.04366***	2064002.*	**25.89135***	26.68660	26.20540
6	-5463.756	11.18629	2163583.	25.93826	26.88498	26.31213
7	-5454.860	16.58905	2237105.	25.97138	27.06958	26.40506
8	-5445.594	17.10625	2309357.	26.00277	27.25245	26.49628

Table 4: VAR Lag Order Selection Criteria

5.4. VAR stability conditions

After deciding on the lag length, we need to check if our VAR(5) process is stable, and thus invertible. This is true when the inverse roots of the characteristic polynomial lie inside the unit imaginary circle. As seen in Figure 6, all inverse roots are within the unit circle, so we conclude that the stability conditions for the VAR(5) process are met.

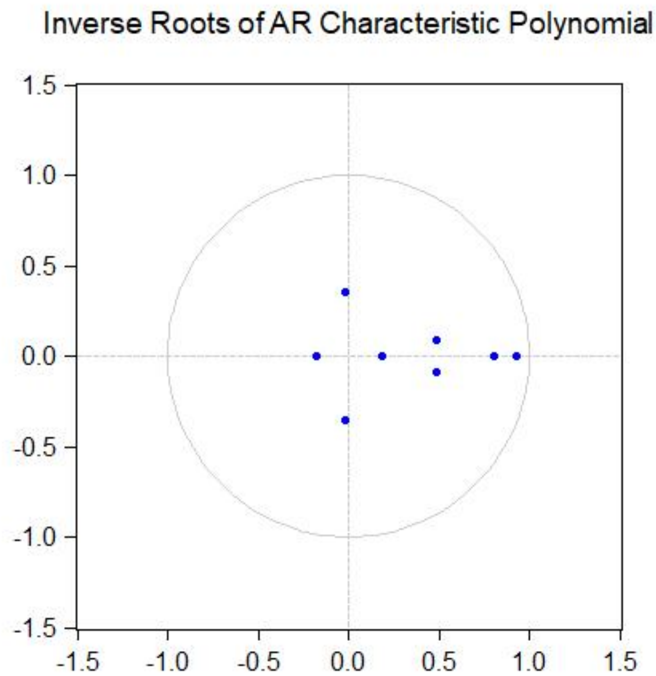

Figure 6: AR inverse roots graph

5.5. Residuals diagnostics

The last step in estimating the VAR model is to ensure that there is no autocorrelation between the residuals. An Autocorrelation LM test is used, and the results are presented in Table 5. The Null Hypothesis of the test is that there is no serial correlation at lag h. Using a 5% significance level, it is suggested that there is autocorrelation in cases of less than 4 lags. For a VAR(5) model, i.e. using 5 lags, it is concluded that there is no concern for autocorrelation of the residuals.

VAR residuals autocorrelation test						
Lag	**LRE* stat**	**df**	**Prob.**	**Rao F-stat**	**df**	**Prob.**
1	36.85835	16	0.0022	2.324229	(16, 1280.7)	0.0022
2	47.61230	16	0.0001	3.014988	(16, 1280.7)	0.0001
3	32.72696	16	0.0080	2.060388	(16, 1280.7)	0.0080
4	24.46819	16	0.0798	1.535491	(16, 1280.7)	0.0798
5	19.14927	16	0.2610	1.199218	(16, 1280.7)	0.2610
6	13.82114	16	0.6120	0.863753	(16, 1280.7)	0.6120
7	13.88899	16	0.6070	0.868016	(16, 1280.7)	0.6070
8	25.59594	16	0.0600	1.606968	(16, 1280.7)	0.0600

Table 5: VAR residuals autocorrelation test results

5.6. Short-term relationship between geopolitical risk and the economy

In this section, the short-term dynamics of geopolitical risk, oil supply, oil demand, and oil futures prices will be analyzed based on our SVAR model which was estimated with the help of the previous steps.

5.6.1. Pairwise Granger Causality tests

To test for causality between the variables of the model, a Granger Causality test is conducted. A summary of the results is presented below in Table 6.

The results of the Granger Causality test show that geopolitical risk does not have a causal relationship with oil futures basis, either as the dependent or independent variable. Using a 5% significance level, we fail to reject the null hypothesis of non-causality in both cases. These results are in line with Huang et al. (2021) who find that geopolitical risk does not Granger cause oil prices, but rather oil price volatility. Also, the geopolitical risk does not Granger causes oil supply and demand.

As expected, there is a causal relationship between oil futures basis and oil supply and demand. To be more specific, there is bidirectional causality between oil futures basis and oil demand, expressed as the global real economic activity. Furthermore, the oil futures basis Granger causes oil supply. As the test results show, we obtain a p-value of less than 0.05, rejecting the null hypothesis of non-causality in these relationships.

Granger causality test results		
Null hypothesis	**Chi-sq**	**p-value**
Oil supply ↛ Geopolitical risk	1.337004	0.9311
Oil demand ↛ Geopolitical risk	7.924871	0.1604
Oil futures basis ↛ Geopolitical risk	6.910483	0.2274
Geopolitical risk ↛ Oil supply	4.623677	0.4635
Oil demand ↛ Oil supply	6.557240	0.2557
Oil futures basis ↛ Oil supply	**19.37793**	**0.0016**
Geopolitical risk ↛ Oil demand	4.441029	0.4878
Oil supply ↛ Oil demand	11.36978	0.0445
Oil futures basis ↛ Oil demand	**11.95089**	**0.0355**
Geopolitical risk ↛ Oil futures basis	4.541453	0.4744
Oil supply ↛ Oil futures basis	9.599157	0.0874
Oil demand ↛ Oil futures basis	**37.41572**	**0.0000**

The symbol "↛" means that variable X does not Granger cause variable Y.

Table 6: Granger causality test results

5.6.2. Impulse Response Functions

Granger causality might not give us the full picture of how the variables in a system interact. Knowing how one variable responds to an impulse in another variable in a system that also includes several other variables is frequently interesting in applied work. In order to better understand the impulse response relationship between two variables in a higher dimensional system, one would like to conduct research (Lütkepohl, 2005). In this section, the Impulse Response Functions are estimated using a structural decomposition provided by our SVAR model.

In the figures presented below, the response of one variable’s volatility to a positive one standard deviation shock in each of the explanatory variables is plotted. The impulse response function illustrates the dynamic response of the variable under investigation to this shock for a 95% confidence interval. Since our data are expressed on a monthly basis, the horizontal axis of the graphs represents the duration of the response's effects in months. The units of the variable under study are shown on the vertical axis. Finally, the line represents the response, and the dotted lines represent a 95% confidence interval for the response. Any impact whose confidence interval includes zero is considered to be non-significant.

In Figure 7 below the responses of geopolitical risk to a one-standard deviation structural shock of the other variables in the model are presented. If we focus on the relationship between geopolitical risk and crude oil futures basis, the graph shows that a structural shock in the Basis creates a positive response on the geopolitical risk that starts 2 months after the shock and lasts for 4 more months. However, these results are not statistically significant, because the zero value is included in the intervals. Structural shocks in oil supply and demand also create non-significant responses to geopolitical risk of small magnitude. The only exception is that geopolitical risk responds negatively to a positive shock in oil demand 3 months after the fact. Based on these results, it is concluded that shocks in the oil market do not have a significant short-term impact on geopolitical risk.

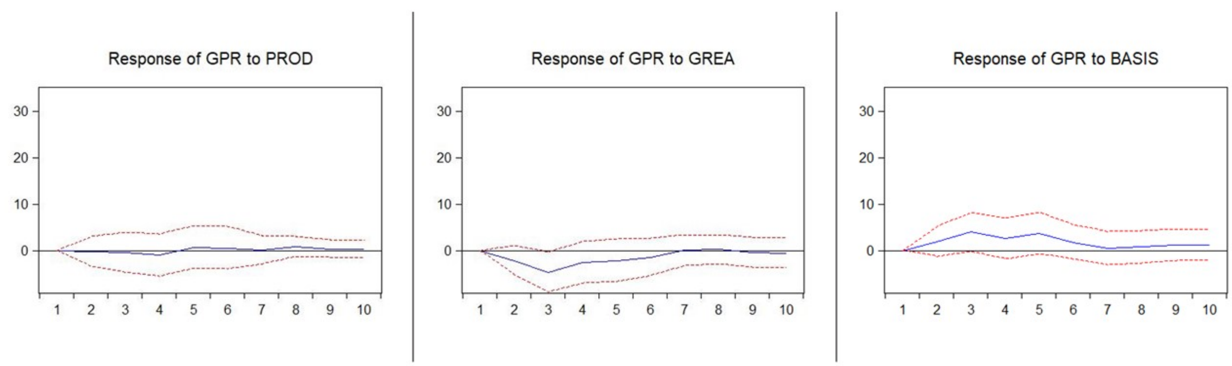

Figure 7: Impulse Response Function of Geopolitical Risk (GPR)

The crude oil futures basis has a significant response to structural shocks in the other variables of the model. As presented in Figure 8, a one-standard deviation structural shock in geopolitical risk yields a significant positive response of almost 2 units to crude oil futures basis 1 month after the shock. The positive effect is statistically significant for 3 months in total. The economic interpretation of this result is that the news of adverse geopolitical events or threats, expressed as a positive shock to the geopolitical risk index, result in an increase in the difference between spot and futures prices in the crude oil market. Economic and political uncertainty affects the anticipation for changes in oil availability in the future. It can be argued that market participants anticipate a disruption in oil supply due to acts or threats that disturb geopolitical stability. Hence, demand for the oil commodity is increased now compared to the near future relative to the available supply, as captured by the increase in the spot price relative to the futures price. From a financial perspective, this increase in the basis, or the "strengthening" of the basis, as a result of a shock in geopolitical risk leads to the improvement of the short hedger's position.

Furthermore, a structural shock in oil production leads to a significant negative response of crude oil basis 1 month after the incident and lasting for 3 months in total. In the last graph, it is observed that crude oil futures basis responds positively to a positive shock in oil demand in the next 2 months until the next 5 months.

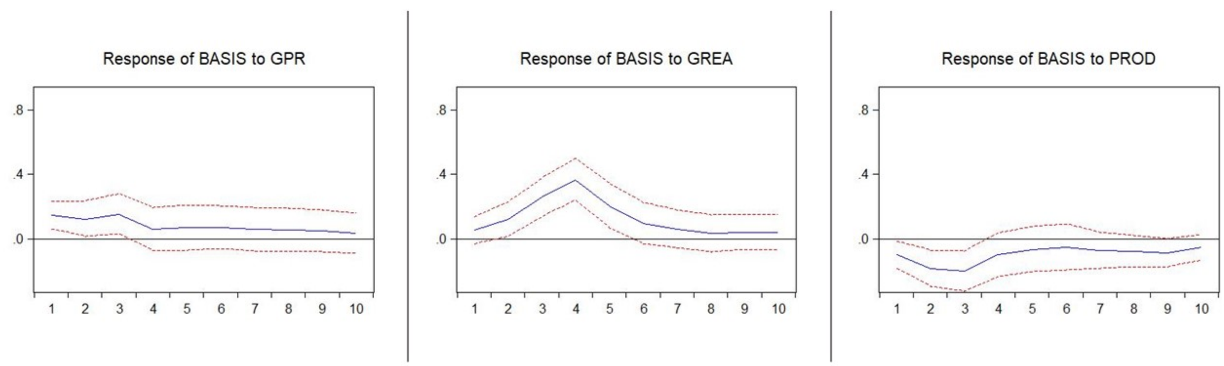

Figure 8: Impulse Response Function of crude oil futures basis (BASIS)

In Figure 9 the response of oil supply, calculated as the percentage change in global crude oil production, is presented. A one-standard deviation structural shock in geopolitical risk has no significant impact on global crude oil production. From the graph, it is clear that the effects of such a shock are of a minor magnitude and are not statistically significant for a 10-month period into the future. However, a structural shock in oil demand results in a small increase in the percentage change of global oil production 4 months after the shock. Furthermore, global oil production has a positive response to a shock in crude oil futures basis. The impact begins 2 months after the shock and lasts until the third month.

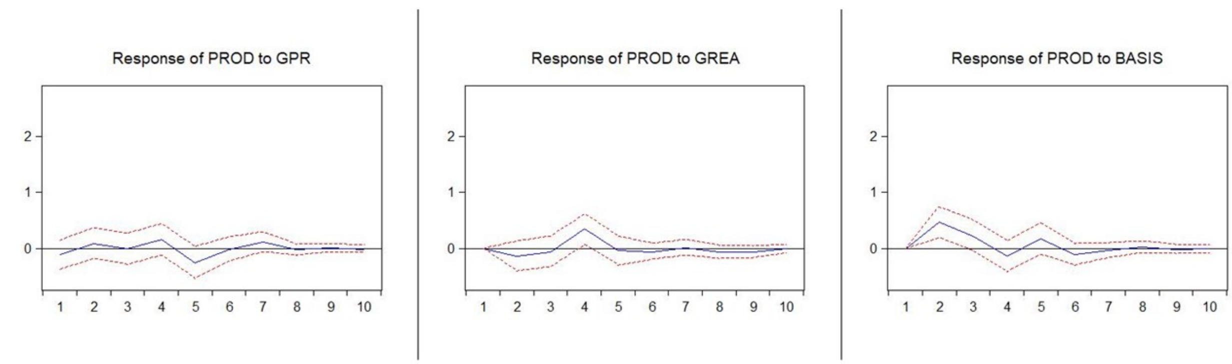

Figure 9: Impulse Response Function of global oil supply (PROD)

As in the case of oil supply, a structural shock in geopolitical risk does not have a statistically significant effect on the global real economic activity index, used here as a proxy for oil demand. Similarly, a one-standard deviation structural shock in global crude oil production yields no significant impact on demand. However, the crude oil futures basis is the only variable with a significant impact on oil demand. A structural shock in crude oil futures basis has a positive impact for 3 months on oil demand. After that period, oil demand seems to decrease and return to normal levels. The graphical representation of these responses is presented in Figure 10 below.

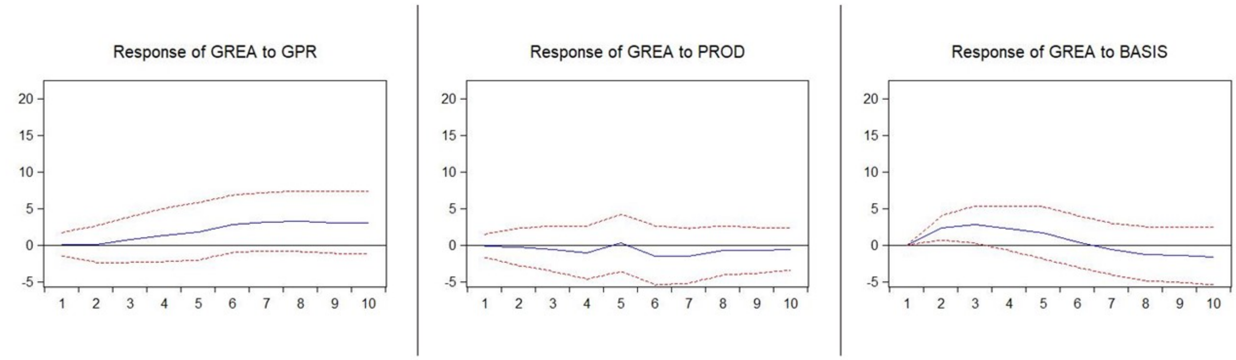

Figure 10: Impulse Response Function of oil demand (GREA)

6. Conclusion

The study will come to a close in this chapter, which will summarize the major results in connection to the objectives and research questions and analyze their importance and contribution. It will also examine the study's weaknesses and suggest areas for future investigation.

Using a Structural Vector Autoregressive (SVAR) model, the short-term dynamics of the oil market were analyzed while accounting for geopolitical risk. The 3-month crude oil futures basis is used as a measure of oil prices, as it effectively captures the anticipation of market participants for price movements. The results of this study show that geopolitical tension has a positive impact on crude oil futures basis, indicating that market participants anticipate a drop in oil prices in the near future compared to the spot market. These results complement the work of Bouoiyou et al. (2019) and Smales (2021) who suggest that increased geopolitical tension positively affects oil prices due to disruptions on the supply side. However, a direct impact of geopolitical risk on oil supply and demand could not be confirmed. Furthermore, statistically significant evidence of a bi-directional relationship between oil prices and geopolitical risk using recent data was not found. These results enrich the ongoing research on the dynamic relationship between geopolitical risk and oil prices, by using recent data to capture the effects of COVID-19 and include new developments in social and economic life.

While the results of this study confirm the significant role of geopolitical risk in analyzing oil price dynamics in recent years, it should be mentioned that only the 3-month crude oil futures basis was used due to data access limitations. This limitation raises the question of how events of geopolitical instability affect oil prices further into the future. The study could be improved by including in the model the prices and basis of 6-month and 12-month crude oil futures. The comparison with the 3-month crude oil futures basis can provide more interesting and complete findings.

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