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**A BIZONYTALANSÁG ÉS A BEJELENTÉSEK HATÁSA AZ ARANY
ÉS OLAJ KAPCSOLATÁRA: MENEDÉK-E AZ ARANY?**

**THE EFFECT OF UNCERTAINTY AND ANNOUNCEMENTS ON
OIL AND GOLD CONNECTEDNESS: IS GOLD A SAFE HAVEN?**

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I. Introduction

The effect of uncertainty on asset returns, volatility or connectedness is a topic extensively researched, but these studies concentrate mainly on the stock market. However, there is growing literature that focuses on commodities, especially the precious metal and oil markets. Commodities in general are special because unlike stocks, bonds and other financial assets, they are physical in nature and used widely in the production of goods, making their price more dependent on traditional demand and supply relations. Both gold and oil have a wide range of uses in the real economy and are two of the most commonly traded commodities with very liquid markets.

Studies showed that oil markets are influenced by economic policy uncertainty (EPU) and geopolitical risk (GPR). Gu et al. (2021) argues that oil is exposed to geopolitical and economic policy uncertainty mainly because of oil supply chains, the geographic location of oil producer countries and volatile market demand. They also showed that EPU has a greater impact on the oil markets.

Gold is widely considered to be an effective diversifier asset and provides a safe haven during economic and financial turmoil. Researchers provided evidence that the two markets are connected and this connection is influenced by uncertainty. Mokni, Hammoudeh, Ajmi and Youssef (2020) concluded that there is a weak average connection between oil shocks and gold markets with a significant increase during crisis periods and the connection is significantly influenced by the EPU. Tiwari et al. (2020) also examined oil-gold relationship and found time-varying Markov tail dependence between gold and oil markets, which is negatively influenced by increasing geopolitical risk.

Due to recent financialization of the oil and gold markets and their increasing acceptability by the investment community (Rehman et al., 2018), there is an ever-growing interest in the dynamics of their connection and the influence of uncertainty measures on the nexus. Since correlation plays a crucial role in asset allocation, portfolio management and risk management, understanding the effect of uncertainty is essential.

The aim of the research is to examine the effect of economic policy uncertainty, geopolitical risk and financial uncertainty on the oil-gold connectedness and provide implications on optimal hedging. The main hypotheses can be summarized as follows:

- 1, Structural oil price shock separation models are necessary in order to better understand the oil-gold nexus.
- 2, The uncertainty indexes have different and nonlinear impact on the different correlations, their effect is regime dependent.
- 3, Gold does not provide a safe haven against oil market risk but acts as a diversifier asset.

4, Both OPEC and FOMC announcements and the COVID-19 pandemic have a significant impact in the nexus.

5, The optimal hedge properties are affected by uncertainty.

To test the validity of the hypotheses, I use the structural oil price shock separation model of Ready (2018), which separates supply (SS), demand (DS) and risk (RS) shocks. The correlation among the series are modeled with the ADCC-GARCH methodology of Cappiello et al. (2006). I test the effect of uncertainty on the connectedness with several regression models, including regular OLS, dummy regression, quantile regression and Markov regime switching model.

The research contributes to the existing literature in the following ways. Firstly, most studies only consider one source of uncertainty, usually economic policy, while I consider several uncertainty measures to better understand the nexus. Secondly, I use the structural model of Ready (2018) to separate oil price movements into disentangled oil price shocks. Thirdly, I examine the effect of OPEC and FOMC announcements, the COVID-19 pandemic and also study the effect of uncertainty on the optimal hedge ratios, portfolio weights and hedging effectiveness.

The results indicate that the uncertainty indexes have a different but significant impact on the oil-gold connection and also highlight the importance of shock separation. Shock-gold connectedness is also influenced by uncertainty and the effect is indeed nonlinear. Both the OPEC and FOMC announcements and the COVID-19 pandemic also have a significant impact. Gold can be considered a diversifier asset against oil returns and oil shocks. During elevated levels of uncertainty, gold does not provide a safe haven against oil market risk. The uncertainty measures affect the optimal hedge properties.

The remainder of the research is organized as follows: Section 2 reviews the related literature. Section 3 describes the methodology used in the research, Section 4 presents the dataset and the preliminary analysis. Section 5 provides and summarizes the empirical findings, Section 6 tests the robustness of the results and Section 7 concludes.

II. Literature review

In the following section, I review the findings of the related literature. Studies that examine the interrelationship between oil and gold markets vary widely in methodology and often provide conflicting results.

The connectedness of oil and gold markets can be explained through different channels. An increase in the price of crude oil increases the production and transportation costs of goods and leads to an increase in inflation. Gold is often used as a hedge against inflation, which makes a positive connection between the two markets (Tiwari and Sahadudheen, 2015). Sari et al. (2010) pointed out that both oil and gold are mostly denominated in US dollars, thus changes in exchange rate affect their price similarly. They also found short-run positive impact of gold price on oil price and vice versa. A third channel was highlighted by Melvin and Sultan (1990), oil-exporting countries include gold in their reserve portfolio, as oil revenues fluctuate, the demand for gold by these countries also fluctuates in order to smooth consumption and government expenditure, making a positive connection between the two markets.

One of the earliest work on the topic was done by Pindyck and Rotemberg (1988), who found that unrelated commodities have a tendency to move together and this phenomenon cannot be explained by fundamental macroeconomic factors. Lescaroux (2009) questioned the work of Pindyck and Rotemberg (1988) and provided evidence using six metals and WTI oil that the high level of correlation among these assets can be explained to a large extent by common shocks to inventory levels.

The comovement between oil and other assets was also studied by Turhan et al. (2014). They showed that there is change in both trend and level of long-run correlation among oil and stock, gold and bond markets with a significant increase after the 2008 financial crisis. This effect can be explained by the increased trading of oil futures and the increasing role of oil as a financial and speculative asset. Charlot and Marimoutou (2014) provided very similar results, the low volatility regimes of oil and gold are associated with low correlations and high volatility regimes with high correlation among the two commodities. S. Kang et al. (2017) provided additional proof that during financial turmoil commodities tend to move in lockstep and presented evidence of a contagion effect.

There seems to be agreement among researchers that the oil and gold markets are connected in some way, the disagreement is related to the direction and whether there is causality in the connection. Studies also examined the casual relationship between oil and metal markets. Sari et al. (2010) found that there is a unidirectional causality from oil price to gold price. Zhang and Wei (2010) showed that there is a long-term equilibrium between the two markets, the oil returns linearly Granger-cause the volatility of gold price, which effect was absent in the nonlinear case, suggesting direct interactive mechanism. Narayan et al. (2010) presented evidence that there is

a long-run relationship between the two markets and they are cointegrated, they also provided further support for the inflation argument of Tiwari and Sahadudheen (2015).

There is a growing literature examining the effect of different uncertainty measures on single assets, asset groups and on the relationship among assets. Baur and Smales (2020) analyzed the effect of geopolitical risk on precious metal returns. They found that GPR positively affects gold, palladium and silver returns. During elevated levels of geopolitical risk, only gold and silver returns are affected by the index. This fact suggests that only these two assets can be considered as a safe haven for those who want to protect their portfolio during elevated levels of geopolitical uncertainty. Joëts et al. (2017) presented that most commodity returns are affected by macroeconomic uncertainty, especially those that are related to business cycles such as agricultural and industrial metals. However, precious metals are less sensitive, indicating their safe haven property.

As I mentioned earlier, exchange rate plays an important role in the connection, both commodities are denominated mainly in US dollars (Sari et al., 2010). Since economic policy strongly affects the exchange rate, the monetary policy of the FED can play an important role in the context. Fasanya et al. (2021) examined the effect of economic policy uncertainty on oil and exchange rate connectivity. They concluded that there is a significant connection between exchange rates and oil markets. Economic policy uncertainty Granger-cause both the conditional mean and the variance of the exchange rates. They provided evidence of the global financial cycle channel, transmissions across the oil and currency pairs being driven by US economic policy uncertainty. These results were further supported by Albulescu et al. (2019), who found that commodity prices generate exchange rate fluctuations, especially in commodity-exporting economies. They also noted that oil is a transmitter of shocks to currency markets and that US monetary policy is a driver of global financial cycle affecting capital flows, credit activity and asset prices.

There are also studies that analyze the effect of uncertainty indexes on stock-commodity correlations. This is an important aspect because of the size of the stock market and investors are liquidating stock positions during high uncertainty periods. Badshah et al. (2019) explored the effect of economic policy uncertainty on stock-commodity connectedness. They found great variations in the correlations, EPU has the most significant positive impact on energy and industrial metals and has a negative impact on precious metal-stock connectedness, the effect is more pronounced during recessionary and high uncertainty periods. Furthermore, Antonakakis et al. (2017) examined oil-stock connection and the effect of geopolitical uncertainty. Only oil markets are sensitive to geopolitical risk according to their work. They argue that stock markets discount geopolitical risk in a more efficient way and the significant effect on oil markets is likely due to the fact that petroleum producing countries are often associated with geopolitical risks, such as the Middle East and Africa.

Gold, silver, palladium and platinum are the four most important precious metals. They are very different when it comes to industrial and investment use. Beyond the previous studies, the interrelationship between precious metals can also be observed. Mokni et al. (2021) using quantile-VAR model present evidence that total connectedness among precious metals increases during extreme market conditions. Economic policy uncertainty has a significant negative effect on total spillover between metals in all quantiles, but changes remarkably during the COVID-19 period. Their results also support the claim made in previous research that gold can be considered a safe haven against economic policy uncertainty.

The suitability of gold to be a safe haven also appeared in Dutta et al. (2020) using a DCC-GARCH model. Their findings suggest that gold is a safe haven for oil markets. During stress periods, there is a strong negative association and during normal times there is a positive association among the two markets. Their result is also supported by the research by Hammoude and Yuan (2008), who examined gold and silver using different GARCH models. Based on their findings, gold and silver have very similar persistence in volatility. These two precious metals are affected by good news, but not bad news. Moreover, oil shocks have a calming effect on these two assets, therefore, they can provide safe haven during volatile periods.

Cryptocurrencies are starting to become an accepted investment alternative, but still lack regulatory and investor confidence aspects. In addition to precious metals, the usage of Bitcoin in hedging strategies against oil market risk has also risen in the previous years, and researchers usually compare the Cryptocurrency with gold. Wu et al. (2019) using GARCH models and quantile regression with dummy variables compared the hedging ability of gold and Bitcoin. They find that both gold and Bitcoin can serve as a weak hedge and weak safe haven against EPU only during extreme bearish or extreme bullish markets. In these circumstances, gold maintains stability with smaller coefficients than Bitcoin. Studying the oil and gold relationship furthermore, Tiwari et al. (2020) using the Markov switching time-varying copula model with wavelet MRA found that the oil-gold dependence is time-varying and has a negative tail asymmetric dependence. They also concluded that the EPU has a negative effect in the medium- and long-term horizons and a positive effect in the short-term horizons. Therefore, gold can be considered a safe haven during extreme market conditions.

Recent studies investigating oil-gold connectedness generally separate oil price shocks on the basis of structural models. These models generally separate at least supply and demand side shocks, but vary in methodology, approach and assumptions.

Using the methodology of Kilian and Park (2009), Rehman et al. (2018) reported a time-varying and different effect of disentangled oil price shocks on precious metal returns. There is moderate connectedness between the two markets, with a sharp increase during the global financial crisis. Their results have also shown that gold seems to have the lowest connectedness among precious metals. W. Kang et al. (2017) also incorporated the same methodology for

oil price shock separation and found that the separated structural shocks explain a great part of the variation in the uncertainty of US economic policy. They showed that oil supply shocks significantly affect CPI forecast uncertainty and expenditure dispersion.

Ready (2018) addresses some of the weaknesses of the structural model of Kilian and Park (2009) and improves it in two ways. Firstly, his model is based on the price of traded assets and using this methodology, shocks can be separated on a daily basis unlike the monthly interval for Kilian and Park (2009). Uddin et al. (2018) adapted the methodology of Ready (2018) using regime-independent and MRS models. Their studies have shown that models with disentangled price shocks have higher explanatory power compared to the undisentangled one. Demand and supply shocks have a positive impact on metal returns, regardless of the regime. They concluded that the regime effect is the strongest in risk shocks and gold return is positively affected by risk shocks.

Another suitable example that compares the hedging effectiveness of Bitcoin and gold is the research from Das et al. (2020), who compared the hedging capabilities of Bitcoin and gold against oil-implied volatility and structural shocks with a GARCH dummy and quantile regression model. They found that gold is not a hedge against OVX (Oil Volatility Index), but a strong safe haven at the upper quantiles. Gold is weakly exposed to demand shocks and acts as a safe haven against supply and risk shocks. They also show that the connectedness is regime dependent.

Demirer et al. (2020) examined the connectedness from a similar aspect using the same methodology for oil price shock separation. They investigated the predicting power of separated shock types on oil realized volatility. They found that disentangled price shocks contain significant information about the future path of volatility of the oil market. The model incorporating the three types of shocks significantly outperformed the rest.

Youssef and Mokni (2021) examined the oil-gold nexus with regime switching-quantile regression. They found that supply and demand shocks have a weak but significant positive impact on gold returns, but risk shocks had no impact with the regular OLS and quantile-based regression model, regardless of the quantile. Using the MRS-QR model they provided widely different results, suggesting that the oil-gold nexus is strongly regime-dependent. In addition, Mokni, Hammoudeh, Ajmi and Youssef (2020), using a TVP-VAR model, have researched the connectedness among the separated oil price shocks and gold returns. They found that there is a weak average connection between separated oil price shocks and gold returns. From their research, it can be seen that the effect is significantly affected by the EPU index. They also found evidence that the effect is symmetric, regime-dependent and more pronounced during financial turmoil.

Using a different model for oil price shock separation based on Baumeister and Hamilton (2019), Oliyide et al. (2021) and Salisu and Adediran (2020) provide conflicting results. The

former present evidence that economic policy uncertainty drives the connectedness between oil shocks and metals. This evidence was based on a spillover model and a causality-in-quantiles test. Their results suggest that gold is a viable asset to hedge against oil price shocks. In contrast, the latter, with the use of bivariate models and cointegration tests, do not favor gold as a hedge against oil price shocks. Irrespective of model, shock type, data or market condition.

Recent trends in the related literature highlight some important considerations in the oil-gold nexus. The first one is the importance of separating oil price changes into structural shocks. If we separate these shocks, we can compare and differentiate the effect of supply- and demand-driven changes. Using this approach, a better understanding of the nexus is possible. The nonlinear and regime-dependent nature of the connection is also an important aspect. If the connection is regime-dependent, linear models are not sufficient and can provide unreliable results. The use of mainly only one uncertainty measure is another weak point, the studies generally only use one measure. Using different uncertainty sources and comparing their effect further insights can be drawn regarding the context.

In the research I keep these aspects in mind. I present the shock separation model and different linear and non-linear regressions in the following section and later the different uncertainty measures.

III. Methodology

In the following sections, I describe the methodology used in the research. The methodology can be separated into four distinct steps. Firstly, I describe the SVAR model of Ready (2018) which is used to separate demand, supply and risk shocks. Secondly, I describe the ADCC-GARCH model, which is used to measure the correlation among the assets. Thirdly, the models used to examine the effect of uncertainty on the connectedness and finally, the hedging calculations are presented.

III.1. Oil price shock construction

There are several studies that examine the oil-gold nexus, but researchers usually do not account for differences in oil price shocks, regardless of the underlying source. To overcome this problem, different structural models were created. A widely used model is from Kilian (2009), the author separating supply and demand driven shocks based on an SVAR model.

Ready (2018) shows the weaknesses of the previous mentioned model, notably the use of oil production as a proxy for supply, shipping activity as a proxy for demand and points out that the included data should correlate contemporaneous or future changes in oil price, and it cannot be ascertained whether these changes in oil price are supply or demand driven.

To address the limitations, he proposes his own framework, where three different shock types are separated, namely: demand, supply and risk shocks, which are based on prices of traded assets. This approach was used by several researchers recently, e.g., Mokni, Hammoudeh, Ajmi and Youssef (2020), Uddin et al. (2018), Das et al. (2020), Dermier et al. (2020) and Youssef and Mokni (2021).

In this study, I follow this methodology. The disentangled shocks are constructed by following the equation:

$$Z_t = A^{-1}X_t$$

$$X_t = \begin{bmatrix} \Delta Poil_t \\ R_t^{Producer} \\ \zeta_{VIX,t} \end{bmatrix} \quad Z_t = \begin{bmatrix} SS_t \\ DS_t \\ RS_t \end{bmatrix} \quad A = \begin{bmatrix} 1 & 1 & 1 \\ 0 & a_{22} & a_{23} \\ 0 & 0 & a_{33} \end{bmatrix}$$

Where Z_t is a vector containing the supply (SS), demand (DS) and risk shock (RS). X_t a vector containing the changes in oil price ($\Delta Poil_t$), the return on the index of oil producing firms ($R_t^{Producer}$) and the innovations in the log of the VIX index based on an ARMA(1,1) process ($\zeta_{VIX,t}$).

In this setting, demand shocks are the returns on the index of oil-producing firms, which are orthogonal to the innovations in the log of the VIX index, which represents changes in market discount rates. Supply shocks are the portion of contemporaneous oil price changes, orthogonal to demand shocks and innovations in the log of the VIX index. By construction, the sum of the three separated shocks account for all the variation in oil price (Ready, 2018).

The intuition behind the model is that oil producers benefit from increased demand, while have a natural hedge against supply shocks. When oil price increase caused by demand, oil producers are able to sell more and experience positive returns. On the other hand, when price increase because the production cost increase, producers sell less at a higher price. Oil producers equity return can be used as a control to determine the source of the shock (Ready, 2018).

III.2. Dynamic conditional correlation: ADCC-GARCH model

In order to measure the conditional correlation between the separated oil price shocks and gold returns, I use the ADCC-GARCH methodology from Cappiello et al. (2006). This model is a generalized version of the standard DCC-GARCH model of Engle (2002). Due to the leverage effect and time-varying risk premia, asymmetry in the volatility of the returns of financial assets may exist. The ADCC model assess this phenomenon and captures the conditional asymmetries in correlation.

The estimation of the model includes a two-step estimation procedure. In the first step, a univariate GARCH model is fitted to the residuals of each time series, from which time varying standard deviations are obtained. In the second step, the standardized residual series are used to estimate the ADCCs. The model is described by Cappiello et al. (2006):

Let r_t be a $k \times 1$ vector of asset returns, assumed to be conditionally normal with mean zero and conditional covariance matrix H_t

$$r_t | \mathfrak{S}_{t-1} \sim N(0, H_t),$$

where $\mathfrak{S}_{t-1}$ is the information available at time $t - 1$. H_t can be decomposed as:

$$H_t = D_t P_t D_t$$

D_t is the diagonal matrix containing the time-varying standard deviations from the univariate GARCH models and P_t is the time-varying correlation matrix.

$$D_t = \text{diag}(h_{1,t}^{1/2}, \dots, h_{n,t}^{1/2})$$

$$P_t = \text{diag}(q_{1,t}^{-1/2}, \dots, q_{n,t}^{-1/2}) Q_t \text{diag}(q_{1,t}^{-1/2}, \dots, q_{n,t}^{-1/2})$$

For the GARCH(1,1) ADCC model $h_{i,t}$ can be written as (Basher and Sadorsky, 2016):

$$h_{i,t} = \omega_i + \alpha_i \varepsilon_{i,t-1}^2 + \beta_i h_{i,t-1} + d_i \varepsilon_{i,t-1}^2 I(\varepsilon_{i,t-1}),$$

where $I(\varepsilon_{i,t-1})$ is an indicator function equal to one if $(\varepsilon_{i,t-1}) < 0$ and zero otherwise. This function is designed to capture the asymmetric effect. Q_t is given by:

$$Q_t = (\bar{Q} - A' \bar{Q} A - B' \bar{Q} B - G' \bar{Q}^- G) + A' z_{t-1} z_{t-1}' A + B' Q_{t-1} B + G' z_t^- z_t'^- G$$

In this equation A,B and G are parameter matrices and z_t^- are zero-threshold standardized errors which are equal to z_t when less than zero and zero otherwise. $\bar{Q}$ and $\bar{Q}^-$ are the unconditional matrices of z_t and z_t^- .

The correlation is estimated as:

$$\rho_{i,j,t} = \frac{q_{i,j,t}}{\sqrt{q_{i,i,t} q_{j,j,t}}}$$

III.3. The effect of disentangled oil price socks on gold returns

OLS regression can only measure the average relationship between gold returns and the separated oil price shocks. To examine the effect on the whole distribution of gold returns, I incorporate the quantile regression model of Koenker and Bassett (1978). The advantage of this model is twofold: it is able to capture the different impact of the independent variables at different market conditions and more robust against outliers, compared to the regular OLS specification. The model can be specified as follows (Ye et al., 2019):

$$y_t = \beta_{0,\tau} + x_t^T \beta_{1,\tau} + \varepsilon_{t,\tau}, \quad t = 1, 2, \dots, n$$

In this model $\beta_{0,\tau}$ and $\beta_{1,\tau}$ are vectors of coefficients associated with the τ -th conditional quantile (Nusair and Olson, 2019), which can be obtained by solving the following minimalization problem (Koenker and Bassett, 1978):

$$L_{\tau,n}(\beta_{\tau}) = \sum_{t=1}^n \rho_{\tau}(y_t - \beta_{0,\tau} - x_t^T \beta_{1,\tau})$$

where ρ_{τ} is a check function defined as:

$$\rho_{\tau}(\mu) = \begin{cases} \tau\mu, & \text{if } \mu \geq 0 \\ (\tau - 1)\mu, & \text{if } \mu < 0 \end{cases}$$

The problem does not have an explicit solution, but can be solved by the interior point algorithm of Koenker et al. (1994).

III.4. The effect of uncertainty on the connectedness

To examine the effect of uncertainty on the estimated ADCCs, I calculate the following regression. A similar approach, where the connectedness measure is regressed on the uncertainty index was also used by Badshah et al. (2019), Mokni, Ajmi, Bouri and VO (2020) and Mokni, Hammoudeh, Ajmi and Youssef (2020).

$$ADCC_t = \beta_0 + \beta_1 EPU_t + \beta_2 GPR_t + \beta_3 VIX_t + \beta_4 REC_t + \beta_5 TERM_t + \beta_6 SPREAD_t + \varepsilon_t$$

In this equation $ADCC_t$ is the estimated conditional correlation from the ADCC-GARCH model at time t . EPU, GPR and VIX are the uncertainty indexes and TERM and SPREAD are the term premium and the credit spread. REC is a dummy variable which takes the value of 1 during recessionary periods and zero otherwise.

Baur and McDermott (2010) distinguish between hedge and safe haven property. Their definition states that a strong (weak) hedge is an asset that is negatively correlated (uncorrelated) with a given asset on average. Strong safe haven is an asset that is negatively correlated (uncorrelated) with another asset in certain periods only, e.g., during financial turmoil. This is an important difference for investors, if an asset is negatively correlated only in crisis periods, investors purchase these assets only during crises, because they do not lose value during these times and provide safe haven.

Baur and Lucey (2010) also define diversifier assets. A diversifier is defined as an asset that is positively (but not perfectly) correlated with another asset or portfolio on average.

To test the safe haven and hedging abilities of gold, a dummy regression is calculated. The methodology is based on Baur and McDermott (2010), but instead of the regression betas I consider the estimated ADCCs in the equation, similarly to Ratner and Chiu (2013), Bouri et al. (2017) and Wang et al. (2020).

$$ADCC_t = \beta_0 + \beta_1 Unc_{1,t}^{0.9} + \beta_2 Unc_{1,t}^{0.95} + \beta_3 Unc_{1,t}^{0.99} + \beta_4 Unc_{2,t} + \beta_5 Unc_{3,t} + \varepsilon_t$$

Where $Unc_{1,t}^{0.9}$, $Unc_{1,t}^{0.95}$, $Unc_{1,t}^{0.99}$ are dummy variables, which takes the value of 1 if the level of the given uncertainty index exceeds the given percentile at day t and zero otherwise. $Unc_{2,t}$ and $Unc_{3,t}$ are the level of the other two uncertainty index at time t .

If the parameters $\beta_0, \beta_1, \beta_2, \beta_3$ are non positive (negative) gold acts as a weak (strong) safe haven. Gold can be considered a weak (strong) hedge if β_0 is zero (negative) and the sum of the parameters $\beta_1, \beta_2, \beta_3$ not jointly positive exceeding the value of β_0 (Baur and McDermott, 2010).

A similar approach was also used by Wu et al. (2019), they tested the safe haven abilities of gold and Bitcoin against EPU. Das et al. (2020) used a similar methodology to test the safe haven abilities of Bitcoin, gold, commodity and US dollar against OVX and separated oil price shocks, based on the methodology of Ready (2018).

The regular OLS assumes linear relationship between the variables. Several studies revealed that there is a nonlinear relationship between commodity returns and the effect of uncertainty on the connectedness is nonlinear as well. To overcome this limitation, I calculate a Markov Regime-switching model which is described as follows (Uddin et al., 2018):

$$ADCC_t = \beta_{0St} + \beta_{1St}EPU_t + \beta_{2St}GPR_t + \beta_{3St}VIX_t + \beta_{4St}TERM_t + \beta_{5St}SPREAD_t + \varepsilon_t$$

where St is a discrete regime variable, β_{0St} is regime-dependent constant and $\beta_{1St}...5St$ are regime-dependent slope coefficients.

The regime switching process follows homogeneous, ergodic, first order Markov chain, with constant transition probabilities and finite number of regimes (M). Assuming that the transition from regime 1 at time t to regime m at time $t + 1$ only dependent on the regime at time t :

$$p_{lm} = Pr(S_{t+1} = m | S_t = l), p_{lm} \geq 0, \sum_{m=1}^M p_{lm} = 1$$

Markov switching models in the oil-gold context was used by Tiwari et al. (2020), Uddin et al. (2018) and Youssef and Mokni (2021).

III.5. Hedging

A useful implication can be derived from the models, a hedging process is created based on the ADCC-GARCH model. On setting up the hedging portfolio the optimal hedge ratio needs to be calculated. The optimal hedge ratio (h_t^*) is calculated as the minimum-variance hedge ratio (Kroner and Sultan, 1993):

$$h_{i,j,t}^* = \frac{h_{ij,t}}{h_{jj,t}}$$

where $h_{ij,t}$ is the conditional covariance between asset i and j at time t and $h_{jj,t}$ is the conditional variance of asset j at time t . In this context, one dollar long position in asset i can be hedged by $h_{i,j,t}^*$ dollar short position in asset j at time t .

The optimal portfolio weights can be calculated minimizing the variance without impacting the expected return, the weight of the hedge asset (gold) in the portfolio is given by (Kroner and Ng, 1998):

$$w_{i,j,t} = \frac{h_{jj,t} - h_{ij,t}}{h_{ii,t} - 2h_{ij,t} + h_{jj,t}}$$

$$w_{i,j,t} = \begin{cases} 0, & \text{if } w_{i,j,t} < 0 \\ w_{i,j,t}, & \text{if } 0 < w_{i,j,t} < 1 \\ 1, & \text{if } w_{i,j,t} > 1 \end{cases}$$

where $h_{ij,t}$ is the conditional covariance between asset i and j at time t, $h_{ii,t}$ and $h_{jj,t}$ are the conditional variance of asset i and asset j at time t and $w_{i,j,t}$ is the optimal weight of the hedge asset at time t.

The hedging effectiveness of the hedge portfolio can be calculated as (Ku et al., 2007):

$$HE = \frac{Var_{unhedged} - Var_{hedged}}{Var_{unhedged}}$$

The HE measures the relative variance reduction in the portfolio and takes a value between zero and one, zero meaning no hedging ability at all, while one indicates perfect hedging.

After the optimal hedge ratios, weights and effectiveness are calculated, I test the effect of uncertainty indexes by computing the following regression:

$$h_t^*; w_{i,j,t}; HE_t = \beta_0 + \beta_1 EPU_t + \beta_2 GPR_t + \beta_3 VIX_t + \varepsilon_t$$

The effect of economic policy uncertainty on the optimal hedge ratios often tested using similar approach. This methodology appeared in testing the effect of EPU on the optimal hedge ratios for different commodities against stock market (Badshah et al., 2019) and also in Bitcoin-stock market nexus (Mokni, Ajmi, Bouri and VO, 2020).

IV. Data and preliminary analysis

In the following section, I describe the data used in the research. Firstly, the three uncertainty indexes which are used in the daily analysis. Secondly, the state of the economy control variables and the alternative uncertainty measures. Finally, the descriptive statistics and preliminary analysis of oil and gold returns and the separated shock types are presented. All of the Figures and Tables presented in the study are own calculations.

IV.1. Uncertainty indexes

Recent studies showed that uncertainty indexes have significant impact on asset returns, volatility and correlation. Since these properties play a crucial role in asset allocation, portfolio- and risk management understanding the effect of uncertainty is essential. These studies usually consider only one uncertainty index.

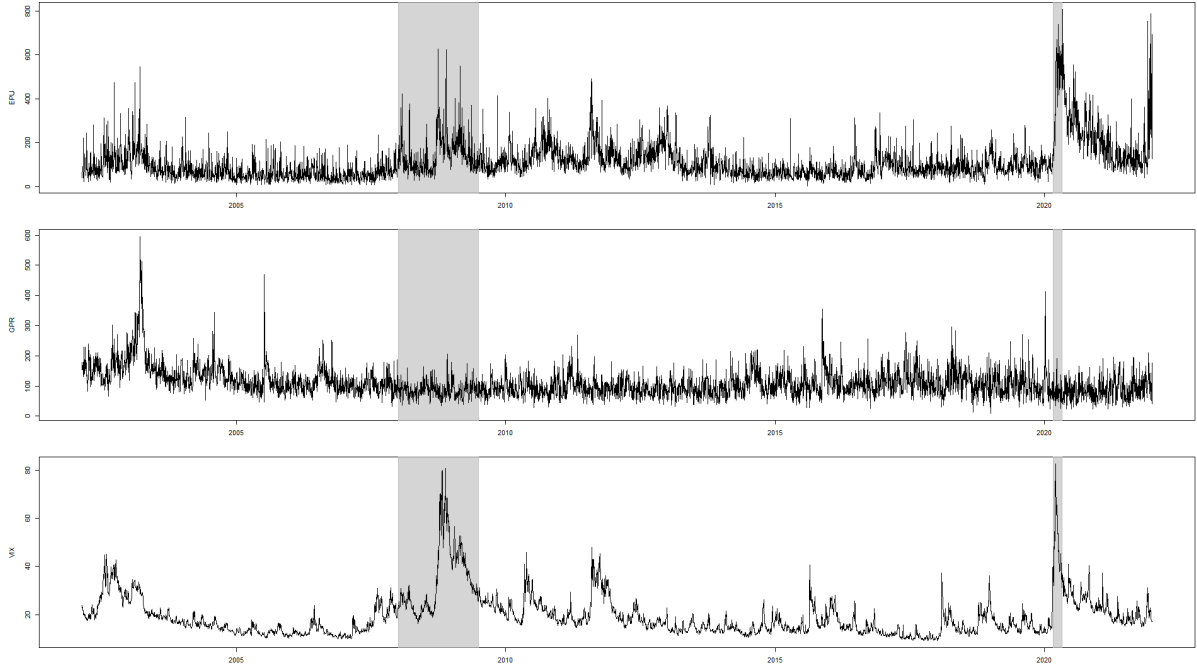
In this research, I take a more comprehensive approach, using three different uncertainty indexes, namely the Economic Policy Uncertainty Index (EPU), the Geopolitical Risk Index (GPR) and the Cboe Volatility (VIX) index.

The EPU is an index constructed by Baker et al. (2016), which has three components. The first component measures policy related uncertainty, based on the textual analysis of newspaper articles associated with policy-related uncertainty. The second component is the number of federal tax code provisions set to expire and the third is the dispersion between forecasters' prediction about macroeconomic variables. EPU is the most commonly used uncertainty index, used by Badshah et al. (2019), Mokni, Ajmi, Bouri and VO (2020), Oliyide et al. (2021) and several others. EPU was obtained from: www.policyuncertainty.com/us_monthly.html.

The GPR index of Caldara and Iacoviello (2018) is created in a similar manner. It quantifies adverse geopolitical events and associated risks based on the textual analysis of newspaper articles. It includes war threats(1), peace threats(2), military buildups(3), nuclear threats(4), terror threats(5), beginning of war(6), escalation of war(7) and terror acts(8). The authors create two sub indexes, Threats (category: 1-5) and actual events (category: 6-8). GPR appeared in the study of Antonakakis et al. (2017), Baur and Smales (2020) and Li et al. (2021). GPR was obtained from: www.matteoiacoviello.com/gpr.htm.

The VIX index measures the 30-day expected volatility of the U.S. stock market, calculated from mid-quote prices of call and put options of the S&P 500 index (Cboe Exchange, 2021). The index is widely used as a proxy for financial stress and uncertainty. The VIX index was obtained from Refinitiv Eikon.

Figure 1: Evolution of the uncertainty indexes



There were several stressed times, during the almost 20-year sample period, recessionary periods are indicated with shaded background in Figure 1. The spikes in the GPR around 2003 are the beginning of the second gulf war, the terrorist attacks in London in 2005 and in Paris at the end of 2015. Both the EPU and VIX shows the end of the dot-com bubble at the end of 2002, the global financial crisis in 2008 and the European sovereign debt crisis starting at 2009. All three series have a great spike at the beginning of 2020, showing the effect of the COVID-19 pandemic. EPU and the VIX index capture similar trends because economic policy has an impact on investor sentiment, which affects the volatility of the stock market. On the other hand, GPR have spikes during different periods, capturing a more distinct and different type of uncertainty.

Table 1: Descriptive statistics of uncertainty indexes

	EPU	GPR	VIX
Mean	111.06	110.06	19.47
Median	88.38	101.27	16.88
Max	807.66	595.03	82.69
Min	3.32	9.49	9.14
Std.Dev	84.44	48.05	8.99
No obs.	5000	5000	5000

IV.2. Control variables

In the research, I utilize several control variables in the daily and monthly frequency analysis. These variables are used as a control for the general state of the economy and describe some relevant conditions that are not captured by the uncertainty indexes. With the use of these variables, it is also possible to filter their effect from the uncertainty indexes and examine the connectedness during certain economic conditions. Most studies do not use control variables, but Badshah et al. (2019) and Baur and Smales (2020) utilize similar variables and highlight their importance.

Most of these control variables are only available at a monthly frequency, therefore only used in the robustness testing section but some of them are calculated on a daily basis.

Following the methodology of Baur and Smales (2020), I include the available control variables in the daily regressions. These variables are the NBER recession index (REC), which takes the value of 1 during recessionary periods and zero otherwise. The average daily yield difference between Moody's AAA and BAA rated bonds (SPREAD) and the daily yield difference on the 2-year and 10-year Treasury securities (TERM). All control variables were obtained from the St. Louis FRED database (fred.stlouisfed.org/).

In the monthly analysis, I include the variables mentioned above and according to Pástor and Veronesi (2013), I also consider the consumer price index (CPI), the Shiller price to earnings ratio for the aggregate stock market (PE) and the growth of industrial production (PROD). CPI and PROD are obtained from the St. Louis FRED database (fred.stlouisfed.org/), PE was downloaded from Shiller's website (www.econ.yale.edu/~shiller/data.htm).

These variables capture economic and stock market related information, which can also play a significant role in the oil-gold nexus.

IV.3. Alternative uncertainty measures

Regarding the effect of uncertainty on the connectivity of oil and gold, the relevant literature often provide conflicting results. In the robustness testing section, monthly correlations are considered. Using a monthly interval, it is possible to use different uncertainty measures, calculated at a monthly frequency. To test the robustness of the results from the daily analysis and provide further insight into the effect. To the best of my knowledge, no one considered these variables in the same context.

These indexes are trade policy uncertainty (TPU) from Caldara et al. (2020), monetary policy uncertainty (MPU) from Husted et al. (2020), financial (FINU) and macroeconomic uncertainty (MACRU) from Jurado et al. (2015), risk aversion (RAV) and economic uncertainty (ECONU) index from Bekaert et al. (2021).

TPU is based on textual research, it measures trade policy related words from transcripts of quarterly earnings of public companies and newspaper articles. It also captures the volatility of import tariff rates based on a stochastic model (Caldara et al., 2020). TPU was obtained from: www.matteoiacoviello.com/tpu.htm.

MPU is also a textual analysis based index, measuring the frequency of monetary policy uncertainty related articles (Husted et al., 2020). MPU was obtained from: www.policyuncertainty.com/hrs_monetary.html.

Financial and macroeconomic uncertainty is based on the VAR forecast error variance decomposition of macroeconomic- and financial indicators and firm-level profit growth by companies (Jurado et al., 2015). The indexes were obtained from: www.sydneyludvigson.com/macro-and-financial-uncertainty-indexes.

Risk aversion and economic uncertainty is based on a dynamic habit model and measures time-varying risk aversion and variations in economic uncertainty (Bekaert et al., 2021). The indexes were obtained from: www.nancyxu.net/risk-aversion-index.

Table 2: Descriptive statistics of alternative uncertainty measures

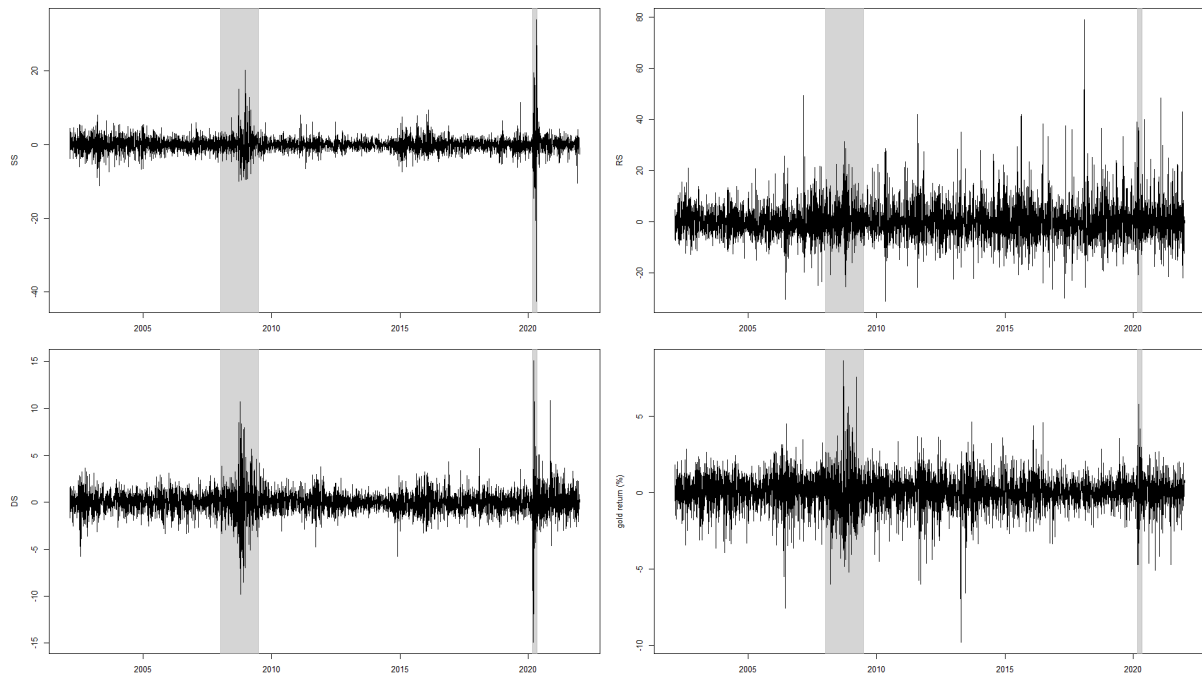
	TPU	MPU	FINU	MACRU	RAV	ECONU
Mean	49.13	121.34	0.9	0.67	3.08	2.21
Median	31	108.55	0.85	0.62	2.81	2.12
Max	266	407.37	1.55	1.27	8.03	4.41
Min	11.3	19.75	0.63	0.53	2.48	1.18
Std.Dev	46.35	68.4	0.19	0.14	0.81	0.51
No obs.	239	239	239	239	239	239

Since all the uncertainty indexes are calculated using different methodology and assumptions, they are not exactly comparable. The main purpose of using these measures is to test if they also have a significant and relatively similar impact on the connection.

IV.4. Preliminary analysis

To disentangle oil price shocks based on the methodology of Ready (2018), three variables are necessary. These variables are changes in oil price, returns on the equity of oil producing firms and changes in market discount rate. I use daily logarithmic returns on the nearest expiry NYMEX -Light Sweet Crude Oil (WTI, CLc1) futures contracts as a representation of changes in oil price. The logarithmic return on the MSCI International ACWI Energy Sector index represents the equity return of oil-producing firms, which includes large and mid-cap oil and gas producer securities across the world. Unexpected changes in the discount rate are derived as the innovations of an ARMA(1,1) process in the log of the CBOE market volatility (VIX) index. The price of gold is represented by the closest expiry COMEX Gold Commodity Futures (GCr1) contracts from which daily continuous compounded returns are calculated. All series were obtained from Refinitiv Eikon, including 5000 daily observations from 2002-02-19 to 2021-12-31; the choice of start and end date is governed by data availability.

Figure 2: Evolution of the separated shock types and gold returns



Witnessing the evolution of the separated shocks, the movements around 2003 most likely due to the conflicts in the Middle East, especially the second Gulf War in Iraq. We can see great movements in the 2008-2009 period, which indicates the effect of the GFC. The spikes in the first part of 2020 show the outbreak of the COVID-19 pandemic. Supply shocks, demand shocks and gold returns follow a similar pattern, suggesting connection between the separated shock types and gold returns.

Table 3: Descriptive statistics of oil and gold returns and the separated shock types

	gold (%)	oil (%)	SS	DS	RS
Mean	0.04	0.03	0	0	-0.01
Median	0.05	0.11	0	-0.01	-0.63
Max	8.64	31.96	33.97	15.11	79.13
Min	-9.82	-60.17	-42.57	-14.92	-31.3
Std.Dev	1.12	2.75	2.29	1.29	7.2
Skewness	-0.36	-2.01	-0.09	0.07	1.22
Kurtosis	5.3	61.31	48.24	15.73	7.19
No obs.	5000	5000	5000	5000	5000
JB	5977***	787091***	485200***	51613***	12041***

Note: Descriptive statistics of daily gold and oil returns and the separated shock types. JB is the Jarque-Bera normality test statistics. *p<0.1; **p<0.05; ***p<0.01

Table 4: Correlation matrix

	gold	oil	SS	DS	RS
gold	1				
oil	-0.003	1			
SS	0.008	0.845	1		
DS	-0.011	0.483	0.000	1	
RS	0.002	-0.208	0.000	0.000	1

The descriptive statistics of oil and gold returns and the separated shocks are presented in Table 3. Gold has the highest return with the lowest deviation and range, making it a possibly ideal risk diversifier asset. Both supply and demand shocks have a mean value of zero, only risk shocks have a mean negative value with the highest deviation. All series have high kurtosis, suggesting a leptokurtic distribution with fat tails. Gold- and oil returns and supply shocks are negatively skewed, whereas demand and risk shocks are positively skewed. The Jarque-Bera test shows, that the null hypothesis of normality is rejected at a 1% significance level for all series.

The gold- and oil returns have a very weak negative correlation during the period. Separated oil price shocks are not correlated, which is expected on the basis of the methodology. Oil returns have a very strong positive correlation with supply shocks, moderately positive with demand and weakly negative with risk shocks, consistent with the findings of Ready (2018), Uddin et al. (2018), and Youssef and Mokni (2021). Moreover, supply- and demand shocks have a stronger relationship with gold returns, which justify the separation of oil price shocks.

Table 5: Testing the preconditions for GARCH modeling

	gold	oil	SS	DS	RS
ADF	-17.5***	-16.1***	-16.5***	-18.7***	-16.7***
KPSS	0.25	0.13	0.07	0.41*	0.24
PP	-71.4***	-75.7***	-76.9***	-66.6***	-70.8***
LBox (20, lin)	0.41	0.52	2.37	3.27*	0.01
LBox (20, sq)	412.8**	1433.6***	24910.6***	3188.3***	49.1***
ARCH-LM (12)	292.64***	737.6***	1474.5***	1160.9***	213.7***

Note: ADF, KPSS and PP are respectively, the statistics of Dickey-Fuller, Kwiatkowski-Phillips-Schmidt-Shin and Phillip-Perron tests. LBox (20, lin) and LBox (20, sq) are the Ljung-Box tests for 20th order serial correlations for returns and squared returns. ARCH-LM (12) is the LM heteroscedasticity test at order 12. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

To model series with the GARCH methodology, there are three necessary properties of the given time series. These properties are stationarity, volatility clustering and presence of ARCH effect. Certain tests can be considered standard regarding these properties, which is used by several research applying GARCH methodology, e.g., Mokni et al. (2021), Antonakakis (2017), Fakhfekh et al. (2021), Youssef and Mokni (2021) and Das et al. (2020).

Table 5. shows the test result of the properties, three types of unit root test is applied, the Augmented Dickey-Fuller (ADF) and the Philippe Peron (PP) tests the null hypothesis of unit root while the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests the null hypothesis of stationarity. On the basis of these results, all series are stationary. Volatility clustering is tested with the linear and squared Ljung-Box test, showing significant autocorrelation for squared returns. All series exhibit ARCH effect, according to the ARCH-LM test.

These results support the ADCC-GARCH modeling approach presented in the latter section of the research.

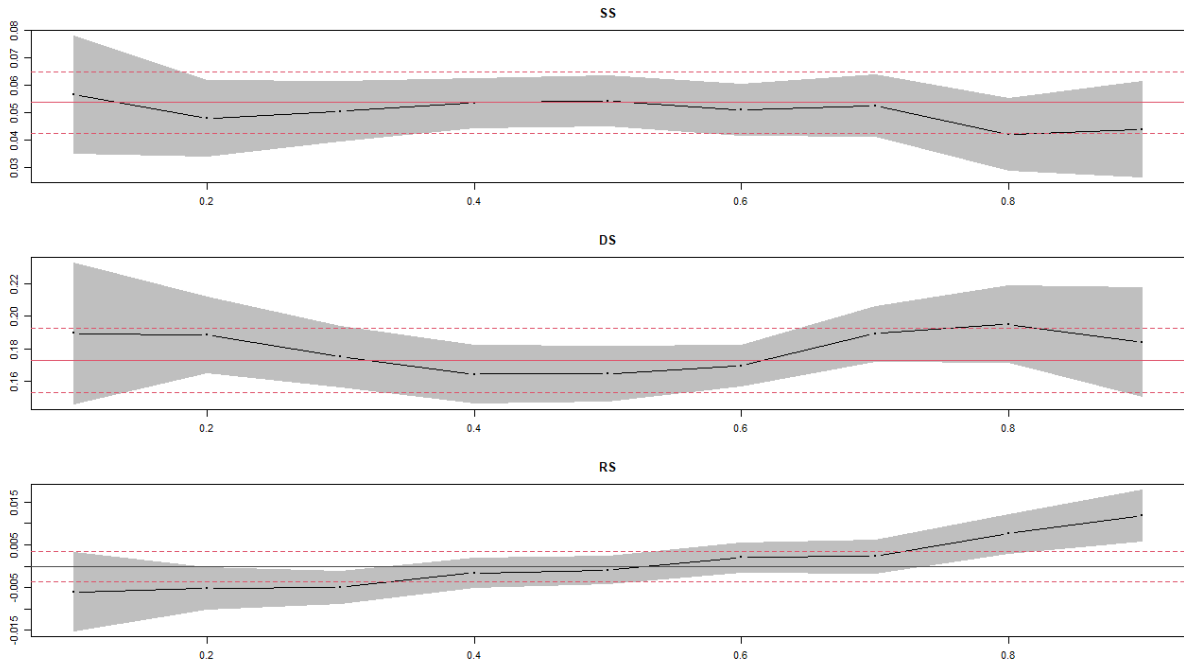
V. Empirical results

In the following section, I present the empirical findings of the research. I test the effect of the separated shock types on gold returns and examine the dynamic conditional correlations obtained from the ADCC-GARCH model. Following that, I study the effect of uncertainty, OPEC and FOMC announcements and the COVID-19 pandemic on the connectedness. In the last part, hedging considerations are provided.

V.1. Effect of oil shocks on gold returns

The first model used in the study is a quantile regression, in which the gold returns are regressed on the separated oil price shocks. The exact same regression was calculated by Youssef and Mokni (2021). Also, Reboredo et al. (2016) used a similar approach to investigate the effect of financial stress and policy uncertainty on different commodity returns.

Figure 3: Quantile regression of oil shocks on gold returns



Quantile regression models assume linear relationship between the separated shocks and gold returns, but are more robust against outliers, compared to the regular OLS specification. Another advantage is that we can see whether the effect of oil price shocks is similar in the whole distribution of gold returns.

Figure 3. shows the results with 95% confidence intervals (grey area) at different quantiles, while the red lines indicate the regular OLS results with 95% confidence intervals (red dashed lines). We can see that demand- and risk shocks both have a weak positive impact on gold returns at every quantile, however, the magnitude of the effect differs among the shocks.

Table 6: Results from quantile regression

	<i>gold return</i>								
	(0.1)	(0.2)	(0.3)	(0.4)	(0.5)	(0.6)	(0.7)	(0.8)	(0.9)
Constant	−1.2005*** (0.0398)	−0.6419*** (0.0207)	−0.3542*** (0.0159)	−0.1330*** (0.0140)	0.0601*** (0.0135)	0.2592*** (0.0154)	0.4891*** (0.0169)	0.7861*** (0.0190)	1.2345*** (0.0261)
SS	0.0567*** (0.0130)	0.0480*** (0.0084)	0.0505*** (0.0066)	0.0537*** (0.0054)	0.0544*** (0.0056)	0.0511*** (0.0056)	0.0526*** (0.0068)	0.0422*** (0.0079)	0.0440*** (0.0106)
DS	0.1894*** (0.0263)	0.1884*** (0.0141)	0.1752*** (0.0113)	0.1645*** (0.0108)	0.1647*** (0.0102)	0.1696*** (0.0077)	0.1892*** (0.0102)	0.1950*** (0.0142)	0.1840*** (0.0202)
RS	−0.0060 (0.0056)	−0.0052* (0.0029)	−0.0050** (0.0023)	−0.0016 (0.0020)	−0.0009 (0.0020)	0.0020 (0.0020)	0.0022 (0.0023)	0.0076*** (0.0028)	0.0119*** (0.0036)
Observations	5,000	5,000	5,000	5,000	5,000	5,000	5,000	5,000	5,000

Note: Entries are the regression coefficients and t-statistics within parenthesis. Results are derived from the regression: $rgold_t = \beta_{0,\tau} + \beta_{1,\tau}SS_t^T + \beta_{2,\tau}DS_t^T + \beta_{3,\tau}RS_t^T + \varepsilon_{t,\tau}$, $t = 1, 2, \dots, 9$ where $rgold_t$ is the gold return and SS, DS, RS are the separated shock types. *p<0.1; **p<0.05; ***p<0.01

Demand shocks have the strongest impact, followed by supply shocks, whereas risk shocks do not seem to have a significant impact except in a few cases at the upper most quantiles. In the case of demand- and supply shocks, the effect is very similar across the entire distribution of gold returns. These results are very similar to the finding of Youssef and Mokni (2021), indicating that there is a stable relationship between gold returns and the separated shocks, which is preferable when we want to model their correlation.

These findings also foreshadow the expected results with respect to the correlation among the series. Since supply and demand shocks have a positive impact on the whole distribution of gold returns, a general positive correlation is expected, with a stronger positive connection in the case of demand shocks and much weaker with risk shocks.

Regression is a static measure, it is unable to capture the variation in time, so in the next section, I overcome this restriction and further examine the connectedness among oil price shocks and gold returns with the ADCC-GARCH model.

V.2. Dynamic correlations

In this section, I present the results from the ADCC-GARCH methodology, which is used to model the correlation among the series. In the first step, an univariate GARCH model was fitted to the return series of gold- and oil returns and the shock types, where the ARMA specification of the mean model was determined by the Bayesian information criterion. All series are modeled with GARCH(1,1) specification. Secondly, the ADCC framework is used to determine the conditional correlations. Different types of GARCH models, investigating the connection between asset returns were also used by Badshah et al. (2019), Dutta et al. (2020), Wu et al. (2019) and Antonakakis (2017).

Figure 4: Estimated ADCCs (black) and rolling-window correlations (red)

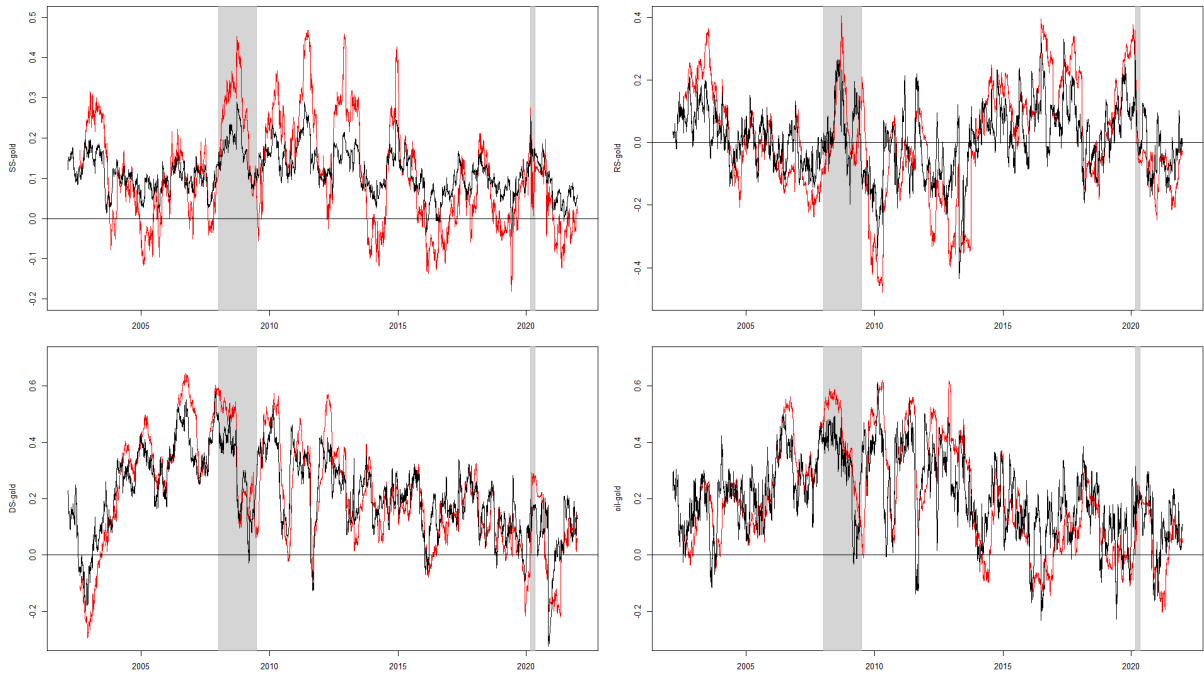


Table 7: Descriptive statistics of estimated ADCCs

	oil	SS	DS	RS
Mean	0.21	0.11	0.21	0.01
Median	0.2	0.11	0.21	0.01
Max	0.61	0.29	0.58	0.34
Min	-0.23	-0.04	-0.32	-0.43
Std.Dev	0.14	0.05	0.15	0.11
No obs.	5000	5000	5000	5000

There is a great variation in the estimated correlations during the sample period. By observing supply- and demand shocks, we can see a general positive relationship almost throughout the entire sample period. Risk shocks exhibit negative correlation more often than the rest of the shock types and seem to have the weakest average correlation. Gold has the most stable relationship with supply shocks. Connectedness varies significantly after the GFC for every series

and it seems that after around 2015 the correlation stays closer to zero.

These results suggest, that the different shock types have different relationships with gold returns, justifying the choice of a structural model. The rolling-window correlation is calculated using a fixed window length of 120 days. The rolling-window correlation is able to capture the relationship between time series, but is often upward biased during volatile periods. To address this limitation, the ADCC-GARCH model is applied. The two series show a similar trend and match relatively well during the period, the rolling correlation seems to be more volatile with higher spikes, whereas the estimated ADCCs are more stable.

The more volatile nature of the rolling correlation is expected, since there is a great agreement among the two methodologies, the estimated ADCCs can be considered to capture the connection among the series correctly, supporting the validity of the ADCC model.

Descriptive statistics are the first hint as to whether gold acts as a hedge- or a diversifier asset. We can see that there is a weak positive average correlation in every case except for risk shocks, where the correlation is very close to zero. Based on these results, gold can be considered a weak hedge against risk shocks and a diversifier for oil returns and the rest of the shock types.

The plots also highlight the necessity of dynamic models when we want to examine the connectedness of different financial markets and time series, in general. The unconditional correlation presented earlier in the research is unable to capture this effect. A generally low correlation can become relatively strong in different circumstances, therefore drawing conclusions based on static measures can be misleading.

V.3. The effect of uncertainty on the connectedness

The results of the baseline regression with the EPU, GPR and VIX index as a proxy for uncertainty are presented in Table 8. The OLS regression is only able to capture the average effect, therefore, it can describe how uncertainty affects the correlation in general. Examining the effect of EPU on stock and commodity market connectedness Badshah et al. (2019) and in the stock market-Bitcoin context Mokni, Ajmi, Bouri and VO (2020) used very similar methodology.

Table 8: Effect of uncertainty on the connectedness

	<i>ADCC</i>			
	oil	SS	DS	RS
Constant	0.2285*** (0.0081)	0.0709*** (0.0027)	0.3636*** (0.0077)	−0.0306*** (0.0061)
EPU	−0.00004 (0.00003)	0.0001*** (0.00001)	−0.0002*** (0.00003)	−0.0001*** (0.00002)
GPR	−0.0001*** (0.00004)	0.00003** (0.00001)	−0.0003*** (0.00004)	0.0006*** (0.00003)
VIX	−0.0032*** (0.0004)	0.0005*** (0.0001)	−0.0058*** (0.0003)	0.0012*** (0.0003)
REC	0.1540*** (0.0099)	0.0471*** (0.0033)	0.1887*** (0.0095)	0.0927*** (0.0074)
TERM	0.0328*** (0.0024)	0.0188*** (0.0008)	0.0156*** (0.0023)	−0.0191*** (0.0018)
SPREAD	0.0008 (0.0077)	−0.0056** (0.0025)	−0.0096 (0.0074)	−0.0218*** (0.0058)
Observations	5,000	5,000	5,000	5,000
R ²	0.0949	0.2299	0.1756	0.1129
Adjusted R ²	0.0938	0.2290	0.1746	0.1119
Residual Std. Error	0.1372	0.0453	0.1313	0.1028
F Statistic	87.2102***	248.4086***	177.2525***	105.9567***

Note: Entries are the regression coefficients and t-statistics within parenthesis. Results are derived from the regression: $ADCC_t = \beta_0 + \beta_1 EPU_t + \beta_2 GPR_t + \beta_3 VIX_t + \beta_4 REC_t + \beta_5 TERM_t + \beta_6 SPREAD_t + \varepsilon_t$ where ADCC is the conditional correlation between gold returns and oil returns or the given shock type. EPU, GPR, VIX are the uncertainty indexes and TERM and SPREAD are the term premium and the credit spread. REC is a dummy variable which takes the value of 1 during recessionary periods and zero otherwise. *p<0.1; **p<0.05; ***p<0.01

The closest comparison to this regression comes from the research by Badshah et al. (2019), who examined the effect of EPU and VIX on stock-commodity correlations. They also used ADCC-GARCH methodology and regressed conditional correlations on both EPU and VIX. They found that VIX is only a determinant in the stock-commodity interrelationship during certain states in the economy. Unlike their findings we can see significant results for VIX in every case, it affects oil and demand shock-gold connectedness positively, while supply- and risk shocks negatively.

Regarding oil and gold connectivity, there are negative coefficients with GPR and VIX. When

geopolitical or financial risk increases, the correlation decreases on average, the results imply that gold could have safe haven property against oil returns and demand shocks. Antonakakis et al. (2017) provided evidence that geopolitical risk has a negative effect on oil returns, while the researches mentioned above showed that gold returns are generally positively affected by uncertainty, from which negative estimates for the coefficients are expected. The results are significant with low R squared values, indicating a very weak connection. As we move to the separated shocks, we can see a general increase in explanatory power, consistent with the findings of Uddin et al. (2018).

Uncertainty seems to affect supply shock-gold connectedness positively and it seems that EPU and VIX have a stronger effect. Regarding risk shocks, a similar pattern is observable except for EPU, which seems to negatively affect the connectedness. All indexes appear to have a negative effect on demand shocks, making gold a possible safe haven asset against demand shocks during elevated levels of uncertainty.

An increase in the EPU and in the VIX index is an indication of financial turmoil, during which investors tend to increase the weight of gold in their portfolio. The increased demand for gold drives the price higher, whereas the decreased demand and liquidation of riskier assets introduce negative demand shocks for oil, explaining the negative coefficients in oil and demand shocks. If oil production is not adjusted in a short window, it can introduce an increase in available supply, making the connection between gold and supply shocks more positive. Risk shocks are unexpected changes in the log of the VIX index, uncertainty most likely increases the implied volatility of options, causing the connection to become stronger.

Since EPU is closely related to the business cycle that affects economic activity, an increase in EPU is associated with lower household consumption and delayed capital investments (Degiannakis et al., 2018), a similar mechanism could be true as in the case of the EPU and VIX index.

To sum up the results, it seems that uncertainty affects the oil-gold and demand shock-gold connectedness negatively, while supply- and risk shock-gold connectedness positively. Based on these results, gold might have some safe haven property against oil returns and demand shocks, but not against supply and risk shocks during elevated levels of economic, geopolitical or financial uncertainty.

Bessembinder and Chan (1992) showed that both the term premium and the credit spread have forecast power in risk premia and futures market prices. Baur and Smales (2020) provided further evidence of this theory, both term premium and credit spread play a significant role in geopolitical risk and asset price correlation. With the inclusion of control variables, we can see that recession and term premium have a positive impact on the connectedness almost in every case, while spread has a less significant negative impact.

An increase in term premium means a steepening yield curve, which is often an indication of growing economic activity and rising inflation. The positive estimates for term premium is likely due to the fact that both commodities are often used as a hedge against inflation, especially gold. Since oil is widely used in the production of goods, growing activity can impose an increase in demand, to which producers could increase their supply. These effects are likely to strengthen the correlation among the series.

An increase in credit spread suggest worsening credit conditions and a decrease in economic confidence, during which investors tend to liquidate commodity positions and fly to safe haven assets like gold, which can explain the negative effect on the correlation.

The positive estimates for the recession dummy is in line with S. Kang et al. (2017), they also found that during financial turmoil commodity returns tend to move in lockstep and presented evidence of contagion effect, diminishing portfolio diversification benefits. Mokni et al. (2021) also presented a similar effect in metal markets, during extreme market conditions the total connectedness among precious metals increases sharply.

Nevertheless, these findings imply that separation of oil price changes into structural shocks is necessary. The uncertainty indexes have different impact, when we consider the source of the underlying shock. To further investigate the effect of uncertainty on the connectedness, the next table shows the results of the extreme dummy regression.

Table 9: Dummy regression with extreme percentiles

ADCC												
	oil	SS	DS	RS	oil	SS	DS	RS	oil	SS	DS	RS
Constant	0.2187*** (0.0068)	0.0749*** (0.0023)	0.3245*** (0.0066)	-0.0706*** (0.0051)	0.2299*** (0.0060)	0.0985*** (0.0021)	0.2989*** (0.0057)	-0.0408*** (0.0044)	0.2066*** (0.0049)	0.0761*** (0.0017)	0.2939*** (0.0047)	-0.0152*** (0.0037)
EPU90	-0.0364*** (0.0096)	0.0057* (0.0033)	-0.0748*** (0.0092)	-0.0172** (0.0071)								
EPU95	-0.0046 (0.0136)	0.0021 (0.0046)	-0.0005 (0.0131)	0.0305*** (0.0101)								
EPU99	-0.0056 (0.0228)	-0.0129* (0.0078)	0.0576*** (0.0220)	0.0031 (0.0169)								
VIX90					-0.0591*** (0.0096)	0.0193*** (0.0033)	-0.1072*** (0.0092)	0.0743*** (0.0070)				
VIX95					0.0082 (0.0136)	0.0071 (0.0047)	0.0248* (0.0131)	0.0049 (0.0100)				
VIX99					0.1262*** (0.0227)	0.0578*** (0.0079)	0.0625*** (0.0217)	0.0327** (0.0165)				
GPR90									-0.0256*** (0.0094)	0.0050 (0.0032)	-0.0611*** (0.0090)	0.0420*** (0.0070)
GPR95									-0.0081 (0.0137)	0.0059 (0.0046)	-0.0328** (0.0131)	0.0272*** (0.0101)
GPR99									0.0383* (0.0228)	0.0069 (0.0077)	-0.0183 (0.0218)	0.0542*** (0.0169)
EPU					-0.00002 (0.00003)	0.0001*** (0.00001)	-0.0003*** (0.00003)	-0.0001*** (0.00002)	-0.0001*** (0.00003)	0.00004*** (0.00001)	-0.0003*** (0.00003)	-0.0001*** (0.00002)
GPR	-0.0002*** (0.00004)	0.00003* (0.00001)	-0.0004*** (0.00004)	0.0005*** (0.00003)	-0.0001*** (0.00004)	0.00003** (0.00001)	-0.0004*** (0.00004)	0.0005*** (0.00003)				
VIX	0.0007*** (0.0002)	0.0018*** (0.0001)	-0.0028*** (0.0002)	0.0011*** (0.0002)					0.0007*** (0.0003)	0.0017*** (0.0001)	-0.0021*** (0.0003)	0.0014*** (0.0002)
Observations	5,000	5,000	5,000	5,000	5,000	5,000	5,000	5,000	5,000	5,000	5,000	5,000
R ²	0.0094	0.1094	0.0870	0.0595	0.0194	0.0798	0.1066	0.0905	0.0058	0.1135	0.0966	0.0458
Adjusted R ²	0.0084	0.1085	0.0860	0.0586	0.0184	0.0789	0.1057	0.0896	0.0048	0.1126	0.0957	0.0448
Residual Std. Error	0.1435	0.0488	0.1382	0.1059	0.1427	0.0496	0.1367	0.1041	0.1437	0.0486	0.1375	0.1066
F Statistic	9.4870***	122.6960***	95.1185***	63.2148***	19.7778***	86.6258***	119.2251***	99.3570***	5.7773***	127.8760***	106.7879***	47.9262***

Note: Entries are the regression coefficients and t-statistics within parenthesis. Results are derived from the regression: $ADCC_t = \beta_0 + \beta_1 U_{nc1,t}^{0.95} + \beta_2 U_{nc1,t}^{0.99} + \beta_3 U_{nc2,t}^{0.95} + \beta_4 U_{nc2,t}^{0.99} + \beta_5 U_{nc3,t}^{0.95} + \beta_6 U_{nc3,t}^{0.99} + \epsilon_t$, where ADCC is the conditional correlation between the gold and the oil returns or the given shock type. Where $U_{nc1,t}^{0.95}$, $U_{nc1,t}^{0.99}$, $U_{nc2,t}^{0.95}$, $U_{nc2,t}^{0.99}$, $U_{nc3,t}^{0.95}$, $U_{nc3,t}^{0.99}$ are dummy variables which take the value of 1 if the level of the given uncertainty index exceeds the given percentile on day t and zero otherwise. $U_{nc2,t}$ and $U_{nc3,t}$ are the level of the other two uncertainty indexes. *p<0.1; **p<0.05; ***p<0.01

To test the effect of extreme uncertainty on the connectedness, dummy variables are included in the regression, these variables are one when the level of the given uncertainty index exceeds the given percentile and zero otherwise. Negative estimates for the dummy variables indicate that during extreme levels of uncertainty the connectedness becomes weaker, thus making gold more suitable as a diversifier asset, indicates possible safe haven properties and also regime-dependent structure in the effect.

With regard to the hedging and diversification ability of gold against oil returns and different types of shock, we can conclude that gold is a diversifier for every series. Reboredo (2013) also showed that gold is neither a hedge nor a safe haven against oil price movements. As was shown earlier, the connectedness among gold and the other series is positive under average conditions. The negative estimates for the constant of risk shocks indicate that gold is the most effective as a diversifier against risk shocks under average conditions, but the sum of the dummy parameters positively exceed the constant almost in every case.

Regarding the safe haven ability of gold, we can conclude that gold does not possess safe haven property against any of the series. The seemingly contradictory results can be explained by the definition of a safe haven asset. A safe haven is defined as an asset that is negatively or uncorrelated with another asset during certain periods (Baur and McDermott, 2010). Other studies define "certain periods" as fall in the stock market or an increase in uncertainty. In this study, certain periods are defined as high levels of economic policy, geopolitical risk or financial uncertainty. I test whether gold can act as a safe haven during these periods against oil shocks or oil returns. So, the question in this study is different from the other researches, what can explain the different results.

Table 10: Average ADCCs during certain periods

	sample	EPU90	EPU95	EPU99	GPR90	GPR95	GPR99	VIX90	VIX95	VIX99	REC
oil	0.207	0.182	0.181	0.182	0.185	0.185	0.213	0.166	0.186	0.287	0.306
SS	0.114	0.137	0.141	0.147	0.123	0.13	0.145	0.148	0.159	0.209	0.169
DS	0.214	0.129	0.127	0.147	0.141	0.116	0.076	0.102	0.122	0.159	0.274
RS	0.009	0.008	0.022	0.016	0.06	0.078	0.115	0.059	0.047	0.023	0.057

Table 10. provides further evidence of the results. The average ADCCs are positive for the entire sample period and for all upper percentiles for every uncertainty measure. In some cases, the average correlation in the upper percentiles is lower than the sample average, but still remains positive. In these cases, gold provides more diversification benefit during elevated levels of uncertainty compared to the average level, but because of the strict definition of a safe haven asset, gold cannot be considered to be one.

Different uncertainty measures affect the dynamic correlations differently in the extreme percentiles and there is no clear pattern. Das et al. (2020) also showed that the hedge and safe haven ability of gold, Bitcoin and the US dollar against oil implied volatility and the separated structural shock types is dependent on the source of oil shock and the general market conditions.

These results indicate that investors should consider not only the driving factor behind the oil price shock, but also the source of uncertainty.

Consistent with recent findings in the literature, significant estimates for the dummies suggest that the effect of uncertainty is dependent on its level, which implies a non-linear relationship. To test this possibility, the Brock, Dechert, and Scheinkman (BDS) test is applied, which was introduced by Broock et al. (1996) and tests whether the residuals are independent and identically distributed. To test the presence of nonlinear effect, the same test was applied by Uddin et al. (2018), Youssef and Mokni (2021) and Fasanya et al. (2021).

Table 11: Results from BDS test

oil					DS			
m	$\epsilon(1)$	$\epsilon(2)$	$\epsilon(3)$	$\epsilon(4)$	$\epsilon(1)$	$\epsilon(2)$	$\epsilon(3)$	$\epsilon(4)$
2	604.60	307.33	217.81	198.31	627.64	308.66	216.93	191.56
3	1105.20	388.79	232.57	194.25	1195.08	392.11	230.83	186.85
SS					RS			
m	$\epsilon(1)$	$\epsilon(2)$	$\epsilon(3)$	$\epsilon(4)$	$\epsilon(1)$	$\epsilon(2)$	$\epsilon(3)$	$\epsilon(4)$
2	504.42	264.57	195.57	176.10	673.30	311.74	211.48	184.94
3	925.91	331.42	207.21	171.83	1281.23	395.68	225.03	180.34

Note: The entries are the BDS test statistics. The parameter m is the embedding dimension and ϵ is the epsilon values for close points. All results are significant at a 1% level.

Table 11. reports the results of the BDS test. The m values represent the embedding dimensions and ϵ represents the distance between the selected pair of points to measure the independent and identical distribution of residuals (Uddin et al., 2018). The null hypothesis of independent and identically distributed residuals is rejected at a 1% significance level for every time series, which is an indication of the non-linear structure of the connection.

Overall, we can conclude that there is strong evidence of a nonlinear relationship, so linear models are unable to capture the effect correctly and maybe suffer from misspecification. To overcome this, a Markov regime switching model is applied, the results are presented in Table 12.

Table 12: Results from MRS model

oil										
Regime	Constant	EPU	GPR	VIX	TERM	SPREAD	std	R ²	TR1	TR2
1	0.3252***	-0.0002***	-0.0002***	-0.001***	0.0374***	0.0167***	0.0761	21%	0.985	0.015
2	0.0936***	-0.0001***	0.0003***	-0.0029***	0.0261***	0.0018	0.0871	13%	0.0128	0.9872
SS										
Regime	Constant	EPU	GPR	VIX	TERM	SPREAD	std	R ²	TR1	TR2
1	-0.0506***	0	0.0001***	-0.0012***	0.005***	0.1697***	0.0188	81%	0.9857	0.0143
2	0.084***	0.0001***	-0.0001***	0.002***	0.0295***	-0.0438***	0.0477	33%	0.0155	0.9845
DS										
Regime	Constant	EPU	GPR	VIX	TERM	SPREAD	std	R ²	TR1	TR2
1	0.2207***	-0.0001***	-0.0001***	-0.0096***	0.0251***	0.0654***	0.0849	33%	0.9941	0.0059
2	0.4366***	-0.0002***	-0.0001	-0.0026***	-0.0004	0.0029	0.074	25%	0.0089	0.9911
RS										
Regime	Constant	EPU	GPR	VIX	TERM	SPREAD	std	R ²	TR1	TR2
1	0.0907***	-0.0003***	0.0004***	0.0052***	-0.1016***	-0.0461***	0.106	39%	0.989	0.011
2	-0.1307***	-0.0001***	0.0004***	-0.002***	0.0537***	0.0571***	0.0408	67%	0.0116	0.9884

Note: Entries are the regression coefficients. The results are derived from a Markov regime switching model: $ADCC_t = \beta_{0Sr} + \beta_{1Sr}EPU_t + \beta_{2Sr}GPR_t + \beta_{3Sr}VIX_t + \beta_{4Sr}TERM_t + \beta_{5Sr}SPREAD_t + \varepsilon_t$ where ADCC is the conditional correlation between gold returns and oil returns or the given shock type. EPU, GPR, VIX are the uncertainty indexes and TERM and SPREAD are the term premium and the credit spread. $\beta_{0Sr}, \beta_{1Sr}, \dots$ are regime dependent intercepts and coefficients. Std is the standard deviation of the state and TR1 and TR2 are transition probabilities. *p<0.1; **p<0.05; ***p<0.01

The MRS model allows the independent variables to switch between regimes, which are determined by a Markov chain. I separated 2 regimes for every time series, the most common number in research, where all of the variables have switching.

EPU does not seem to have a strong regime effect, it has a negative impact on the connectedness in every case, except in regime two in supply shocks and insignificant in regime one. It also has very similar coefficients across regimes and shock types. Mokni, Hammoudeh, Ajmi and Youssef (2020) showed that dynamic spillovers between the separated shock types and gold also regime dependent, both the sign and magnitude of the effect of EPU on the total dynamic connectedness changes between states. The conflicting results can be related to the different methodology, spillover and correlation is a very different measure and the effect of other control and uncertainty variables.

GPR has a strong regime effect in oil-gold connectedness and also in supply shocks where it changes sign. It has a significant effect in regime one on demand shocks but is not significant in regime two, while it does not have a regime effect in risk shocks. Tiwari et al. (2020) also provided evidence that GPR has a regime-dependent effect on oil gold connectedness, using the Markov-switching time-varying copula model. They showed that GPR tends to have a negative impact on medium- and long-term but positive impact on short-term investment horizons.

VIX is the most regime-dependent uncertainty measure, changes sign in supply- and risk shocks and has a different magnitude of negative effect in oil returns and demand shocks. Both term premium and credit spread have strong regime effect, changing sign in risk shocks and spread also in supply shock-gold context. In the demand shock-gold connection, both term premium and credit spread are significant in one regime and insignificant in the other, the same is true for spread in oil-gold correlation.

The standard deviation represents the volatility of the given regime, in oil-gold and demand shock-gold context deviation is almost the same in both regimes, while in the case of supply and especially in risk shocks there is a great variation across regimes. There is a great increase in explanatory power when the regime-switching framework is used compared to the linear models, but we can see great variation in r-squared values across regimes. This result indicates that the overall effect of uncertainty is regime dependent, in a certain regime uncertainty drives the correlation more than in the other regime, which effect was also highlighted by Youssef and Mokni (2021).

It seems that during low volatility regimes, when the connection is more stable, the variables generally explain more of the changes in the correlation than in the higher volatility regime. These results suggest that during normal times the explanatory variables have a more pronounced impact on the linkage between the assets.

An MRS model is considered a good fit when it has transition probabilities close to zero or one (Uddin et al., 2018). All of the probabilities are really close to either 0.99 or 0.01 for every series, suggesting stable regimes.

The results imply non-linearity in the relationship and regime dependence of the effect of uncertainty in the oil-gold nexus.

V.4. Do OPEC announcements matter?

Several studies explored the effect of OPEC announcements and found significant impact on crude oil price (Demirer and Kutan, 2010; Lin and Tamvakis, 2010) and on crude oil volatility (Schmidbauer and Rösch, 2012). Due to the high integration of oil markets and the fact that OPEC is a major player in global oil production, it is interesting to see whether the OPEC announcements have a significant impact in the oil-gold nexus.

Table 13: Effect of OPEC announcements

	<i>ADCC</i>			
	oil	SS	DS	RS
Constant	0.2248*** (0.0081)	0.0705*** (0.0027)	0.3605*** (0.0078)	−0.0284*** (0.0061)
EPU	−0.00004 (0.00003)	0.0001*** (0.00001)	−0.0002*** (0.00003)	−0.0001*** (0.00002)
GPR	−0.0001*** (0.00004)	0.00003** (0.00001)	−0.0003*** (0.00004)	0.0006*** (0.00003)
VIX	−0.0032*** (0.0004)	0.0005*** (0.0001)	−0.0059*** (0.0003)	0.0012*** (0.0003)
REC	0.1479*** (0.0099)	0.0456*** (0.0033)	0.1838*** (0.0095)	0.0941*** (0.0075)
TERM	0.0336*** (0.0024)	0.0191*** (0.0008)	0.0163*** (0.0023)	−0.0190*** (0.0018)
SPREAD	0.0037 (0.0077)	−0.0054** (0.0025)	−0.0071 (0.0074)	−0.0243*** (0.0058)
OPEC (cut)	−0.0208 (0.0166)	−0.0015 (0.0055)	−0.0127 (0.0160)	0.0302** (0.0125)
OPEC (increase)	−0.0255 (0.0201)	−0.0309*** (0.0066)	−0.0081 (0.0193)	−0.0568*** (0.0151)
OPEC (maintain)	−0.0064 (0.0109)	−0.0061* (0.0036)	−0.0039 (0.0105)	−0.0049 (0.0082)
OPEC (no agreement)	0.1270*** (0.0186)	0.0311*** (0.0062)	0.0974*** (0.0179)	−0.0324** (0.0140)
Observations	5,000	5,000	5,000	5,000
R ²	0.1039	0.2376	0.1807	0.1175
Adjusted R ²	0.1021	0.2361	0.1790	0.1157
Residual Std. Error	0.1365	0.0451	0.1310	0.1026
F Statistic	57.8685***	155.5007***	110.0119***	66.4310***

Note: Entries are the regression coefficients and t-statistics within parenthesis. Results are derived from the regression: $ADCC_t = \beta_0 + \beta_1 EPU_t + \beta_2 GPR_t + \beta_3 VIX_t + \beta_4 REC_t + \beta_5 TERM_t + \beta_6 SPREAD_t + \beta_7 OPECdecision_t + \varepsilon_t$ where *ADCC* is the conditional correlation between gold returns and oil returns or the given shock type. *EPU*, *GPR*, *VIX* are the uncertainty indexes and *TERM* and *SPREAD* are the term premium and the credit spread. *REC* is a dummy variable which takes the value of 1 during recessionary periods and zero otherwise. *OPECdecision_t* is a categorical variable which takes the value of the decision type: cut, increase, maintain or no agreement. *p<0.1; **p<0.05; ***p<0.01

The effect of OPEC announcements on oil market returns is well documented. Loutia et al. (2016) studied the effect of OPEC announcements on Brent and WTI returns. They reported expected results, an increase in target production drives prices down, but this effect usually not

significant. The target reduction has a more significant positive impact and is present after the announcement date. The absence of a change in quotas has the most significant negative impact. Furthermore, Klein (2018) examined the effect of OPEC announcements on the interconnection between WTI and Brent oil. On the basis of his results, a high but highly volatile correlation is present and long-term movements are driven by the same dynamics between the two assets. He also provided evidence that OPEC meetings increase the correlation in the short term between the two oil benchmarks.

During the sample period there were 69 OPEC announcements, these include regular and extraordinary meetings. Most of the meetings, 34 ended with agreement to maintain production, 10 with the decision to increase, 14 to decrease production and 11 ended without agreement. The data was obtained from Bloomberg and the classification is based on the change in the target production following Spencer and Bredin (2019). The dummy variables take the value of the decision type on the announcement date and on the previous and following two working days.

Generally speaking, the decision to maintain and cut production does not have a significant impact in the context. Spencer and Bredin (2019) pointed out the importance to separate agreement to maintain production and failure of agreement, previous studies usually categorize both as maintain production. Their findings also suggest that the difference is important and has a different impact on the oil term structure.

It seems that failure of agreement has the strongest impact, it has a positive effect in every case except risk shocks, failing to agree might introduce oil market-related uncertainty in the market, driving oil prices higher. A possible explanation can be the inflation channel (Tiwari and Sahadudheen, 2015), an increase in oil price can increase inflation expectations and investors tend to use gold against inflation, driving the connectedness stronger. Increase in production has a negative impact on supply- and risk shocks, most likely such announcements drive the oil prices lower. Producers can sell more oil on a lower price, introducing a negative supply shock, making the correlation weaker.

Overall, it can be concluded that the change in the target production is not what matters, the most significant is whether the OPEC members can come to an agreement. The effect is most likely related to expectations about future oil supply.

V.5. Do FOMC announcements matter?

Federal Open Market Committee (FOMC) is one of the three key federal reserve entities. FOMC sets the US national monetary policy by conducting open market operations. The Committee affects the Federal Funds rate, at which depository institutions lend to each other (www.federalreserve.gov/monetarpolicy/fomc.htm). Researches showed that FOMC announcements have a significant impact on energy market prices (Rosa, 2014; Jang and Seo, 2020), oil market volatility (Marfatia et al., 2021), precious metal prices (Chebbi, 2021) and the correlation between stock and bond markets (Bodilsen et al., 2021; Cieslak and Pang, 2021). Since monetary policy is a subcategory of economic policy and it affects every part of the economy, the effect of FOMC announcements is an important consideration.

Table 14: Effect of FOMC announcements

	<i>ADCC</i>			
	oil	SS	DS	RS
Constant	0.2280*** (0.0081)	0.0711*** (0.0027)	0.3602*** (0.0077)	−0.0104* (0.0060)
EPU	−0.00003 (0.00003)	0.0001*** (0.00001)	−0.0002*** (0.00003)	−0.0001*** (0.00002)
GPR	−0.0001*** (0.00004)	0.00003** (0.00001)	−0.0003*** (0.00004)	0.0005*** (0.00003)
VIX	−0.0033*** (0.0004)	0.0004*** (0.0001)	−0.0060*** (0.0003)	0.0008*** (0.0003)
REC	0.1474*** (0.0100)	0.0455*** (0.0033)	0.1824*** (0.0095)	0.0942*** (0.0074)
TERM	0.0343*** (0.0024)	0.0190*** (0.0008)	0.0171*** (0.0023)	−0.0153*** (0.0018)
SPREAD	0.0041 (0.0077)	−0.0047* (0.0026)	−0.0067 (0.0073)	−0.0312*** (0.0057)
FOMC (increase)	0.0154 (0.0124)	−0.0006 (0.0041)	0.0374*** (0.0117)	−0.0165* (0.0092)
FOMC (decrease)	0.0574*** (0.0157)	0.0143*** (0.0052)	0.0344** (0.0149)	0.0103 (0.0116)
FOMC (no change)	−0.0185*** (0.0060)	−0.0044** (0.0020)	−0.0148*** (0.0057)	0.0033 (0.0045)
Observations	5,000	5,000	5,000	5,000
R ²	0.0995	0.2319	0.1798	0.0936
Adjusted R ²	0.0979	0.2305	0.1784	0.0920
Residual Std. Error	0.1368	0.0453	0.1299	0.1015
F Statistic	61.2528***	167.3768***	121.5750***	57.2791***

Note: Entries are the regression coefficients and t-statistics within parenthesis. Results are derived from the regression: $ADCC_t = \beta_0 + \beta_1 EPU_t + \beta_2 GPR_t + \beta_3 VIX_t + \beta_4 REC_t + \beta_5 TERM_t + \beta_6 SPREAD_t + \beta_7 FOMCdecision_t + \varepsilon_t$ where $ADCC$ is the conditional correlation between gold returns and oil returns or the given shock type. EPU , GPR , VIX are the uncertainty indexes and $TERM$ and $SPREAD$ are the term premium and the credit spread. REC is a dummy variable which takes the value of 1 during recessionary periods and zero otherwise. $FOMCdecision_t$ is a categorical variable which takes the value of the decision type: increase, decrease, no change. *p<0.1; **p<0.05; ***p<0.01

There were 162 FOMC announcements during the sample period. The decoding of the announcements is based on the change in the Federal Funds target rate. Most of the announcements left the target rate unchanged, 119 to be exact. The FOMC increased the rate 26 times and decreased 17 times. The data was obtained from Bloomberg, the dummies take the value of the decision on the announcement date and the previous and following two working days.

The decision to increase the target rate only have a positive significant impact on demand shock-gold connectedness. The decision to decrease or if the rate left unchanged have a different significant impact on oil, supply- and demand shock gold connection. Marfatia et al. (2021) concluded that monetary policy uncertainty significantly affect the oil markets, during heightened policy uncertainty periods FOMC announcements have a lower impact on oil market returns and volatility.

Increase in interest rates can increase the costs of production and the export of goods, imposing negative demand shocks for oil. Abdullah and Bakar (2015) showed that real gold price is inversely related to real rates, hence nominal rates are positively related to commodity prices, which is also known as Gibson's Paradox. When the FED increases the interest rates the price of gold decreases. These two effects can increase the correlation among the two series.

When the FOMC announces the decrease in the rate, market participants expect a depreciation in the US dollar and can interpret it as an indication of worsening economic conditions. During these circumstances the demand for gold increases because investors want to protect the value of their portfolio. Askari and Krichene (2010) argues that oil demand is mainly driven by income, decrease in interest rates expand economic activity and the demand for oil, driving oil prices higher. Ready (2018), showed that supply shocks have a strong negative relation with future economic output, explaining the positive estimates for supply shocks.

The significant estimates for the announcements, when the FOMC did not changed the rate, can be explained by the fact that futures prices are driven by expectations. Interest rates during most of the sample period were really low, so investors could not really expect further decrease in the rates. When participants expect increase, but it does not happen, the inflation expectations increase, driving gold prices higher. Jang and Seo (2020), found that policy rate changes affects energy prices before the FOMC announcements and only the anticipated changes have such effect. The energy market volatility increases on announcement dates only if investors expect negative policy rate change. Since the rates remained unchanged and the expectations could not be negative, the announcements most likely have stronger positive impact on gold prices and left oil markets relatively unchanged, these effects can explain the negative estimates when the rates left unchanged.

V.6. Effect of COVID-19

Recent studies investigated the effect of the COVID-19 pandemic on financial markets (Ali et al., 2020) and the hedging ability and safe haven property of gold (Akhtaruzzaman et al., 2021; Dutta et al., 2020; Mensi et al., 2021; Salisu et al., 2021). The researches concluded that the pandemic had a significant impact on the connection between oil and gold markets, in this section, I examine the effect of the COVID-19. The start of the pandemic is considered to be 2020-01-30, when the WHO declared the outbreak a Public Health Emergency of International Concern (WHO, 2020).

Table 15: Effect of COVID-19 pandemic

	<i>ADCC</i>			
	oil	SS	DS	RS
Constant	0.2541*** (0.0081)	0.0807*** (0.0027)	0.3944*** (0.0075)	0.0012 (0.0061)
EPU	0.0001*** (0.00003)	0.0001*** (0.00001)	−0.00004 (0.00003)	−0.00001 (0.00002)
GPR	−0.0002*** (0.00004)	0.000000 (0.00001)	−0.0004*** (0.00004)	0.0005*** (0.00003)
VIX	−0.0016*** (0.0004)	0.0011*** (0.0001)	−0.0038*** (0.0003)	0.0016*** (0.0003)
REC	0.1580*** (0.0097)	0.0486*** (0.0032)	0.1900*** (0.0090)	0.0968*** (0.0073)
TERM	0.0245*** (0.0024)	0.0156*** (0.0008)	0.0043* (0.0022)	−0.0189*** (0.0018)
SPREAD	−0.0376*** (0.0080)	−0.0201*** (0.0026)	−0.0604*** (0.0074)	−0.0499*** (0.0060)
COVID-19	−0.1111*** (0.0080)	−0.0423*** (0.0026)	−0.1501*** (0.0074)	−0.0529*** (0.0060)
Observations	5,000	5,000	5,000	5,000
R ²	0.1283	0.2676	0.2388	0.1067
Adjusted R ²	0.1271	0.2666	0.2377	0.1054
Residual Std. Error	0.1346	0.0442	0.1237	0.1007
F Statistic	104.9977***	260.5963***	223.7000***	85.1485***

Note: Entries are the regression coefficients and t-statistics within parenthesis. Results are derived from the regression: $ADCC_t = \beta_0 + \beta_1 EPU_t + \beta_2 GPR_t + \beta_3 VIX_t + \beta_4 REC_t + \beta_5 TERM_t + \beta_6 SPREAD_t + \beta_7 COVID_t + \epsilon_t$ where ADCC is the conditional correlation between gold returns and oil returns or the given shock type. EPU, GPR, VIX are the uncertainty indexes and TERM and SPREAD are the term premium and the credit spread. REC is a dummy variable which takes the value of 1 during recessionary periods and zero otherwise. COVID is a dummy variable which takes the value of 1 from 2020-01-30 to 2021-12-31 and zero otherwise. *p<0.1; **p<0.05; ***p<0.01

We can see significant negative results for the COVID-19 dummy in all cases. Sharif et al. (2020) showed that the outbreak had a significant impact on both GPR and EPU. They also provided evidence that the COVID-19 and related regulatory responses are sources of both economic policy and geopolitical risk and also had a significant effect on oil prices.

Due to the pandemic, several countries imposed quarantine, travel and trade restrictions around

the world. People were working from home, not allowed to travel abroad and forced to stay home. As a result, the demand for fuel and therefore oil decreased significantly, driving oil prices lower and introducing negative demand shocks to the oil market. Ali et al. (2020) showed that gold was relatively stable during the outbreak, while the crude oil markets experienced some of its most uncertain periods due to the pandemic and also from the reactions of oil producers. Explaining the negative effect on the connectedness.

The stock market also experienced some of its most turbulent periods since the GFC, the S&P 500 fell significantly, introducing panic and increasing risk aversion. Investors looked for safe haven assets, increasing the demand for gold. As a result the correlation between oil and gold returns was further decreased. Dutta et al. (2020) also found that during the pandemic period, the correlation between oil and gold decreased significantly and showed that gold acted as a safe haven asset during the early periods of the health crisis. Salisu et al. (2021) also presented similar results, both the optimal weight of gold in the hedge portfolio and the hedging effectiveness increased sharply.

V.7. Hedging

In the previous sections, evidence was presented that the oil-gold connectedness is affected by uncertainty, a practical implication of which is hedging oil exposure with gold. Badshah et al. (2019) and Mokni, Ajmi, Bouri and VO (2020) also took a similar approach, examining the effect of uncertainty on optimal hedge ratios.

Table 16: Effect of uncertainty on hedge properties

	h^*	W_{gold}	HE
Constant	0.3179*** (0.0154)	0.7767*** (0.0058)	0.7682*** (0.0016)
EPU	0.0004*** (0.0001)	0.00004 (0.00002)	0.00004*** (0.00001)
GPR	-0.00002 (0.0001)	0.0002*** (0.00004)	0.0002*** (0.00001)
VIX	0.0033*** (0.0006)	0.0021*** (0.0002)	-0.0002*** (0.0001)
Observations	5,000	5,000	4,940
R ²	0.0284	0.0320	0.0715
Adjusted R ²	0.0278	0.0314	0.0709
Residual Std. Error	0.3215	0.1220	0.0330
F Statistic	48.5954***	54.9900***	126.6681***

Note: Entries are the regression coefficients and t-statistics within parenthesis. Results are derived from the regression: $h_t^*; w_{i,j,t}; HE_t = \beta_0 + \beta_1 EPU_t + \beta_2 GPR_t + \beta_3 VIX_t + \varepsilon_t$ where h_t^* , $w_{i,j,t}$, HE_t are the optimal hedge ratio, weight of gold and hedging effectiveness respectively. EPU, GPR, VIX are the uncertainty indexes. *p<0.1; **p<0.05; ***p<0.01

Table 17: Hedge properties during certain periods

	sample	EPU90	EPU95	EPU99	GPR90	GPR95	GPR99	VIX90	VIX95	VIX99	REC	COVID-19
h^*	0.424	0.503	0.616	1.111	0.42	0.437	0.562	0.466	0.54	0.799	0.668	0.369
W_{gold}	0.843	0.871	0.89	0.97	0.87	0.879	0.904	0.869	0.902	0.946	0.893	0.854
HE	0.79	0.799	0.802	0.8	0.811	0.814	0.827	0.792	0.776	0.756	0.76	0.837

Based on previous results, gold can be considered a diversifier asset in an oil portfolio. Gold returns have a positive but not perfect correlation with oil returns on average. Mensi et al. (2021) also concluded that Brent oil is a diversifier against precious metals from 1997 to the end of 2019.

An increase in the optimal hedge ratio and portfolio weight means that more money should be invested in the hedge asset, making hedge more expensive and less attractive to investors. The increase in uncertainty increases the optimal hedge ratio, which implies that greater hedge positions are necessary to minimize risk. Badshah et al. (2019) found that EPU affects optimal hedge ratios in stock-gold and stock-oil connectedness negatively, I find that EPU affects oil-gold connectedness positively, so overall these results are consistent with their findings. GPR does not seem to have a significant effect on the hedge ratio, while VIX also has a positive

impact. During stock market crises, investors increase the weight of gold in their portfolio to minimize downside risk (Reboredo, 2013).

The hedge ratio and optimal weight describe how the portfolio is created to minimize risk exposure. The hedging effectiveness describes the reduction in the variance of the hedge portfolio compared to the unhedged portfolio. HE is calculated as a rolling window hedging effectiveness of 60 days. Both EPU and GPR have a positive impact on HE, which means that during elevated levels of uncertainty, the diversification benefits from gold investments increase. However, VIX has a negative impact, which means that during high levels of financial uncertainty, gold does not provide as much diversification benefit, which is likely due to the contagion effect (S. Kang et al., 2017).

The optimal weight of gold in the hedge portfolio during the sample period is 0.84, meaning that for every 1 dollar of portfolio, 84 cents should be invested in gold and only 16 in oil. Although it is possible, it makes hedging very expensive. The 0.84 average optimal weight of gold is exactly the same as reported by Salisu et al. (2021) in the same context, who also showed that during the COVID-19 period there is an increase in optimal weight, which is also consistent with my results.

Regarding gold's safe haven ability, we can see that during high uncertainty and recessionary periods, both the ratio and weight increase, meaning that gold does not have safe haven ability against oil returns during elevated periods of economic policy, geopolitical, financial uncertainty or recessionary periods.

Since separated shock types are not investable assets, the methodology is not suitable to determine the optimal ratios and weights against the separated shock types.

In summary, the uncertainty indexes affect the optimal hedge ratio, portfolio weight and hedging effectiveness. Gold is an effective but expensive diversifier asset in an oil portfolio, without safe haven properties. It can reduce oil market risk with increasing efficiency during elevated levels of uncertainty.

VI. Robustness and additional tests

In the following sections, I test the robustness of the results and provide some additional tests, working with daily and monthly data. Since monthly EPU and GPR are calculated as the average of the daily values during the month, the monthly correlations are calculated as the average of the daily correlations.

VI.1. Is the effect symmetric?

It is a well known phenomenon that bad news usually have a greater impact on stock market returns. Using the methodology of Kilian (2009), Atems et al. (2015), found evidence that the exchange rates respond differently to positive and negative oil price shocks. Clements et. al. (2019) showed similar asymmetric effect in the equity markets. On the other hand, Mokni, Hammoudeh, Ajmi and Youssef (2020) did not found asymmetric effect between oil price shocks and gold returns. In this regression, I separated positive and non-positive shocks and tested, if the uncertainty indexes have the same impact regardless of the sign of the shock.

Table 18: Effect of positive and negative shocks

	ADCC positive shocks				ADCC negative shocks			
	oil	SS	DS	RS	oil	SS	DS	RS
Constant	0.2237*** (0.0116)	0.0692*** (0.0039)	0.3701*** (0.0104)	-0.0188** (0.0085)	0.2335*** (0.0113)	0.0731*** (0.0037)	0.3387*** (0.0105)	-0.0042 (0.0084)
EPU	-0.00003 (0.00004)	0.0001*** (0.00001)	-0.0002*** (0.00003)	-0.0001** (0.00003)	-0.0001 (0.00004)	0.0001*** (0.00001)	-0.0002*** (0.00003)	-0.0001*** (0.00003)
GPR	-0.0001 (0.0001)	0.00004** (0.00002)	-0.0003*** (0.0001)	0.0005*** (0.00005)	-0.0002*** (0.0001)	0.00002 (0.00002)	-0.0003*** (0.0001)	0.0005*** (0.00004)
VIX	-0.0041*** (0.0006)	0.0004** (0.0002)	-0.0061*** (0.0005)	0.0013*** (0.0003)	-0.0026*** (0.0005)	0.0005*** (0.0002)	-0.0053*** (0.0004)	0.0003 (0.0004)
REC	0.1470*** (0.0141)	0.0415*** (0.0046)	0.1885*** (0.0129)	0.0963*** (0.0101)	0.1605*** (0.0139)	0.0532*** (0.0047)	0.1684*** (0.0128)	0.0940*** (0.0106)
TERM	0.0358*** (0.0034)	0.0197*** (0.0011)	0.0123*** (0.0031)	-0.0091*** (0.0026)	0.0304*** (0.0033)	0.0180*** (0.0011)	0.0184*** (0.0030)	-0.0192*** (0.0024)
SPREAD	0.0105 (0.0113)	-0.0051 (0.0037)	-0.0136 (0.0101)	-0.0416*** (0.0079)	-0.0059 (0.0106)	-0.0061* (0.0035)	-0.0003 (0.0099)	-0.0216*** (0.0082)
Observations	2,612	2,504	2,486	2,243	2,388	2,496	2,514	2,757
R ²	0.0948	0.2218	0.1846	0.0956	0.0984	0.2405	0.1679	0.0959
Adjusted R ²	0.0927	0.2200	0.1826	0.0931	0.0962	0.2387	0.1659	0.0939
Residual Std. Error	0.1393	0.0455	0.1265	0.0977	0.1347	0.0452	0.1240	0.1043
F Statistic	45.4539***	118.6466***	93.5359***	39.3702***	43.3308***	131.3832***	84.2994***	48.6127***

Note: Entries are the regression coefficients and t-statistics within parenthesis. Results are derived from the regression: $ADCC_t = \beta_0 + \beta_1 EPU_t + \beta_2 GPR_t + \beta_3 VIX_t + \beta_4 REC_t + \beta_5 TERM_t + \beta_6 SPREAD_t + \varepsilon_t$ where ADCC is the conditional correlation between gold returns and oil returns or the given shock type. EPU, GPR, VIX are the uncertainty indexes and TERM and SPREAD are the term premium and the credit spread. REC is a dummy variable which takes the value of 1 during recessionary periods and zero otherwise. *p<0.1; **p<0.05; ***p<0.01

There is a very similar pattern, however there are some differences. It seems that oil-gold connectedness is only affected by GPR, when the shocks are negative, the opposite is true for supply shock-gold connectedness. VIX generally have a very similar impact in oil and demand shocks, but it has stronger negative to positive oil returns and insignificant to negative risk shocks. The other variables have generally the same impact regardless of the sign of the shock. Mokni, Hammoudeh, Ajmi and Youssef (2020) also concluded that the spillovers from positive and negative oil price shocks to gold returns are very similar, the effect is symmetric.

Furthermore, they showed that EPU has very similar impact on the spillovers regardless of the sign of the shock.

Overall, we can conclude that the uncertainty indexes have symmetric impact on the connect-
edness, the sign of the shocks does not play a significant role in the context.

VI.2. Threats or events?

As I mentioned earlier in the study, Caldara and Iacoviello (2018) create two sub-indexes of their GPR measure. These subindexes are geopolitical threats in contrast to actual geopolitical events. The threats subindex is an indication of increasing geopolitical tension without actual events happening, while the events only measure incidents that are actually occurred. The distinction between the two category is important and have a different impact on precious metal returns (Baur and Smales, 2020), energy commodity volatility (Liu et al., 2021) and on the volatility spillovers in oil and stock markets (Smales, 2021). The studies suggest that the threats have stronger, while the actual events usually have much weaker or insignificant impact.

Table 19: GPR threats or actual events

	<i>ADCC</i>			
	oil	SS	DS	RS
Constant	0.2324*** (0.0080)	0.0726*** (0.0026)	0.3714*** (0.0076)	−0.0057 (0.0059)
EPU	−0.00003 (0.00003)	0.0001*** (0.00001)	−0.0002*** (0.00003)	−0.0001*** (0.00002)
GPR (events)	0.00005 (0.00003)	0.00004*** (0.00001)	0.0001* (0.00003)	0.0002*** (0.00002)
GPR (threats)	−0.0002*** (0.00004)	−0.00001 (0.00001)	−0.0004*** (0.00004)	0.0003*** (0.00003)
VIX	−0.0031*** (0.0004)	0.0005*** (0.0001)	−0.0057*** (0.0003)	0.0008*** (0.0003)
REC	0.1543*** (0.0099)	0.0471*** (0.0033)	0.1896*** (0.0095)	0.0951*** (0.0073)
TERM	0.0312*** (0.0024)	0.0183*** (0.0008)	0.0128*** (0.0023)	−0.0153*** (0.0018)
SPREAD	−0.0018 (0.0077)	−0.0062** (0.0026)	−0.0147** (0.0074)	−0.0320*** (0.0057)
Observations	5,000	5,000	5,000	5,000
R ²	0.0975	0.2311	0.1855	0.0922
Adjusted R ²	0.0962	0.2300	0.1843	0.0910
Residual Std. Error	0.1370	0.0453	0.1312	0.1015
F Statistic	77.0014***	214.3086***	162.3931***	72.4662***

Note: Entries are the regression coefficients and t-statistics within parenthesis. Results are derived from the regression: $ADCC_t = \beta_0 + \beta_1 EPU_t + \beta_2 GPR_{events_t} + \beta_3 GPR_{threats_t} + \beta_4 VIX_t + \beta_5 REC_t + \beta_6 TERM_t + \beta_7 SPREAD_t + \varepsilon_t$ where ADCC is the conditional correlation between gold returns and oil returns or the given shock type. EPU, GPR, VIX are the uncertainty indexes and TERM and SPREAD are the term premium and the credit spread. REC is a dummy variable which takes the value of 1 during recessionary periods and zero otherwise. *p<0.1; **p<0.05; ***p<0.01

With the disaggregation of the GPR index, we can see that the perceived threats have more significant impact on oil returns and demand shocks, while insignificant in supply shocks. Interestingly, the events and threats have very similar effect on risk shock-gold connectedness, only in this case have both subindex significant effect. Baur and Smales (2020) tested the effect of actual geopolitical events and threats on the returns of precious metals. They showed that only the perceived risks have a significant impact on the returns, what can explain the mostly significant impact for the threats.

Futures prices are mainly driven by the investors expectations about the future, not the actual events. The significant impact of threats in demand shock-gold connectedness further support the argument, since investors are increasing the demand for gold when they perceive possible risks and impose negative demand shock for oil markets because of the more volatile nature of oil.

The significant estimates of the events in supply shock-gold connectedness, likely because oil producers are not interrupting their production until they are not forced to do so. Increase in possible threats does not affect the ability of these companies to produce and transport oil, but when the events materialize they can have significant impact. This is especially true, since the greatest spikes in the GPR index is associated with wars and other significant events in oil producing countries, like the occupation of Iraq and Afghanistan. Bouoiyour et al. (2019) also concluded that the actual geopolitical events have significant impact on oil markets, because the events are what cause disruption in oil-producing countries and making the availability of oil supply questionable.

VI.3. State of economy control variables

Using monthly returns, I am able to use a wider range of control variables to further examine the oil-gold nexus and to check, whether the effect still exists on a monthly frequency. Baur and Smales (2020) also conducted a similar analysis in precious metal markets, following the work of Pástor and Veronesi (2013).

Table 20: Monthly correlations with state of economy control variables

	<i>ADCC</i>			
	oil	SS	DS	RS
Constant	0.9025*** (0.1237)	0.2336*** (0.0438)	1.2582*** (0.1107)	−0.1895** (0.0941)
EPU	−0.0003* (0.0002)	0.0001 (0.0001)	−0.0005*** (0.0002)	0.0002* (0.0001)
GPR	−0.0005* (0.0003)	0.0001 (0.0001)	−0.0012*** (0.0003)	0.0012*** (0.0002)
VIX	0.0005 (0.0019)	0.0009 (0.0007)	−0.0030* (0.0017)	−0.0023 (0.0014)
REC	0.1615*** (0.0446)	0.0524*** (0.0158)	0.1772*** (0.0399)	0.1148*** (0.0339)
TERM	−0.0093 (0.0118)	0.0078* (0.0042)	−0.0279*** (0.0105)	−0.0077 (0.0090)
SPREAD	−0.1255*** (0.0380)	−0.0391*** (0.0135)	−0.1330*** (0.0340)	0.0074 (0.0289)
NAI	0.0029 (0.0063)	0.0013 (0.0022)	0.0002 (0.0056)	0.0066 (0.0048)
CPI	−0.0006 (0.0005)	−0.00003 (0.0002)	−0.0013*** (0.0005)	0.0002 (0.0004)
PE	−0.0137*** (0.0030)	−0.0048*** (0.0011)	−0.0131*** (0.0027)	0.0014 (0.0023)
PROD	0.8955 (0.6890)	0.0200 (0.2442)	0.5441 (0.6166)	−1.1773** (0.5242)
Observations	239	239	239	239
R ²	0.2770	0.3250	0.4626	0.2094
Adjusted R ²	0.2453	0.2954	0.4390	0.1748
Residual Std. Error	0.1179	0.0418	0.1055	0.0897
F Statistic	8.7356***	10.9781***	19.6268***	6.0404***

Note: Entries are the regression coefficients and t-statistics within parenthesis. Results are derived from the regression: $ADCC_t = \beta_0 + \beta_1 EPU_t + \beta_2 GPR_t + \beta_3 VIX_t + \beta_4 REC_t + \beta_5 TERM_t + \beta_6 SPREAD_t + \beta_7 NAI_t + \beta_8 CPI_t + \beta_9 PE_t + \beta_{10} PROD_t + \varepsilon_t$ where $ADCC$ is the conditional correlation between gold returns and oil returns or the given shock type. EPU, GPR, VIX are the uncertainty indexes, TERM, SPREAD, NAI, CPI, PE, PROD are term premium, credit spread, national activity, consumer price index, price to earnings ratio and industrial production growth. REC is a dummy variable which takes the value of 1 during recessionary periods and zero otherwise. *p<0.1; **p<0.05; ***p<0.01

Based on Pástor and Veronesi (2013), I consider the following control variables. AAA/BAA corporate bond default spread (SPREAD), Fed National Activity Index (NAI), Consumer Price Index (CPI), Shiller's Price-to-Earnings ratio for the aggregate stock market (PE), Industrial Production Growth (PROD) and the NBER recession dummy (REC), which is one during the

recession months and zero otherwise.

On the monthly interval, spread, price-to-earnings ratio and recession is the most important determinant of the connectedness. While the former two have a negative impact, the REC dummy has a positive effect. The results for spread and recession are consistent with the findings on the daily observations. In general, high price-to-earning ratios mean that investors are willing to pay more for stocks, indicating bullish market conditions and confidence in the market, during which investors are more likely to liquidate gold portfolios and buy riskier assets. The demand for oil and the output is usually high in such states, imposing positive demand shocks and driving oil prices higher.

Uncertainty indexes seem to have a less pronounced effect in most cases at a monthly interval. EPU only affects demand shocks positively, and GPR seems to affect both demand and risk shocks, the former negatively and the latter positively. Since the uncertainty indexes are calculated as the average uncertainty of the month, these results are not unexpected. On the one hand, the other control variables might account for the effect also included in the uncertainty indexes. The values of the indexes are less volatile when we calculate average levels and they are not aligned well enough with the events (Baur and Smales, 2020), making their effect less pronounced on the monthly interval.

Regarding the other variables, unlike in the daily interval, the term premium does not have a significant effect. The same is true for national activity and the CPI except in demand shocks, an increase in price levels drives the demand for oil lower.

Based on these results, we can conclude that the alignment is very important in this context, uncertainty indexes are more volatile compared to the other measures, which are less likely to change significantly on a daily frequency.

In the next model, alternative measures of uncertainty are considered and their effect on the connectedness is compared.

VI.4. Alternative measures of uncertainty

There are other uncertainty measures which are calculated on a monthly basis. In the following regression, I consider these alternative uncertainty indexes. Since the goal of this section is to test that other indexes trying to capture similar types of uncertainty have a similar effect, I exclude EPU, GPR and VIX. To the best of my knowledge, no one considered these indexes in the oil-gold correlation context. However one or more of these indexes appeared in studies, which examined the effect of uncertainty on gold markets (Beckmann et al., 2019; Balcilar et al., 2016; Bouoiyour et al., 2018) and on crude oil volatility (Li et al., 2022).

Table 21: Alternative uncertainty measures

	<i>ADCC</i>			
	oil	SS	DS	RS
Constant	0.2816*** (0.0465)	0.0624*** (0.0166)	0.4192*** (0.0465)	−0.0993*** (0.0348)
TPU	−0.0005** (0.0002)	−0.0002** (0.0001)	−0.0006*** (0.0002)	−0.00003 (0.0002)
MPU	−0.0006*** (0.0001)	−0.0002*** (0.00005)	−0.0005*** (0.0001)	0.0005*** (0.0001)
FINU	−0.0194 (0.0819)	0.0883*** (0.0293)	−0.2313*** (0.0819)	0.0073 (0.0613)
MACRU	0.0578 (0.0835)	−0.0416 (0.0298)	0.1429* (0.0834)	−0.0551 (0.0625)
RAV	−0.0254 (0.0209)	0.0019 (0.0074)	−0.0424** (0.0209)	−0.0107 (0.0156)
ECONU	0.0389 (0.0279)	0.0107 (0.0100)	0.0569** (0.0279)	0.0533** (0.0209)
Observations	239	239	239	239
R ²	0.1914	0.2340	0.2484	0.1444
Adjusted R ²	0.1705	0.2142	0.2290	0.1223
Residual Std. Error	0.1236	0.0441	0.1236	0.0925
F Statistic	9.1528***	11.8145***	12.7786***	6.5254***

Note: Entries are the regression coefficients and t-statistics within parenthesis. Results are derived from the regression: $ADCC_t = \beta_0 + \beta_1 TPU_t + \beta_2 MPU_t + \beta_3 FINU_t + \beta_4 MACRU_t + \beta_5 RAV_t + \beta_6 ECONU_t + \varepsilon_t$ where $ADCC$ is the conditional correlation between gold returns and oil returns or the given shock type. TPU, MPU, FINU, MACRU, RAV, ECONU are trade policy, monetary policy, financial and macroeconomic uncertainty, risk aversion and economic uncertainty. *p<0.1; **p<0.05; ***p<0.01

Trade policy uncertainty has a negative effect in all cases. One of the most common use of oil in the economy is to produce fuel, which affects both demand and supply of oil. Caldara et al. (2019) argues that an increase in trade policy uncertainty lowers real investments, consumption and export activity. Less export activity drives the demand for oil lower and uncertainty about real-economy investments might drive the demand for safer investment alternatives like gold higher.

Monetary policy uncertainty is a subcategory of economic policy uncertainty. An increase in

MPU has a very similar effect as the TPU. Husted et al. (2020) pointed out that increase in monetary policy uncertainty delay firm investments, lowers output and also causes increase in credit spread. From the previous regression, we can already see that credit spread has a negative impact on oil-gold connectivity.

Financial uncertainty generally has the same impact as the VIX index. The stronger impact of financial uncertainty compared to macro uncertainty is likely due to the financialization of these commodities and their usage in portfolio diversification, as Rehman et al. (2018) noted. Risk aversion is closely associated and strongly correlated with equity risk premium and predicts output growth negatively (Bekaert et al., 2021). VIX index is often used as a proxy for the attitude toward risk and we can similar but less significant effect as the VIX index.

The results generally show similar patterns regardless of the source of uncertainty. The connectedness between gold-oil and gold-demand shocks is negatively affected, while the risk shocks are positively affected by uncertainty. The least consistent results are found for supply shocks.

These results further emphasize the importance of uncertainty and that the choice of the uncertainty measures is important, but also support the argument that the correlation between the markets is affected by uncertainty.

VI.5. Different residual distribution assumptions

In the previous analysis, the residual error distribution was assumed to be normal. In this section, the results of the previous ADCC model are compared with the Student's t error distribution. Misspecification of the error distribution can affect the efficiency of estimators and could lead to invalid results (Klar et al., 2012). Researchers usually consider Student's t or different asymmetric t-distributions as an alternative to the normal distribution (Lyu et al., 2017; Filis et al., 2011; Basher and Sadorsky, 2016; Mensi et al., 2016).

Table 22: ADCC specification with normal and Student's t error distribution

	ADCC normal				ADCC Student's t			
	oil	SS	DS	RS	oil	SS	DS	RS
Constant	0.2285*** (0.0081)	0.0709*** (0.0027)	0.3639*** (0.0078)	-0.0110* (0.0060)	0.2208*** (0.0076)	0.0712*** (0.0022)	0.3719*** (0.0083)	-0.0110* (0.0060)
EPU	-0.00004 (0.00003)	0.0001*** (0.00001)	-0.0002*** (0.00003)	-0.0001*** (0.00002)	-0.00004 (0.00003)	0.0001*** (0.00001)	-0.0002*** (0.00003)	-0.0001*** (0.00002)
GPR	-0.0001*** (0.00004)	0.00003** (0.00001)	-0.0003*** (0.00004)	0.0005*** (0.00003)	-0.0001*** (0.00004)	0.00002 (0.00001)	-0.0003*** (0.00004)	0.0005*** (0.00003)
VIX	-0.0032*** (0.0004)	0.0005*** (0.0001)	-0.0058*** (0.0003)	0.0008*** (0.0003)	-0.0030*** (0.0003)	0.0005*** (0.0001)	-0.0062*** (0.0004)	0.0008*** (0.0003)
REC	0.1540*** (0.0099)	0.0471*** (0.0033)	0.1890*** (0.0095)	0.0949*** (0.0073)	0.1541*** (0.0093)	0.0349*** (0.0027)	0.1883*** (0.0102)	0.0949*** (0.0073)
TERM	0.0328*** (0.0024)	0.0188*** (0.0008)	0.0158*** (0.0023)	-0.0150*** (0.0018)	0.0337*** (0.0022)	0.0172*** (0.0007)	0.0164*** (0.0024)	-0.0150*** (0.0018)
SPREAD	0.0008 (0.0077)	-0.0056** (0.0025)	-0.0096 (0.0074)	-0.0316*** (0.0057)	0.0056 (0.0072)	0.0008 (0.0021)	-0.0097 (0.0079)	-0.0316*** (0.0057)
Observations	5,000	5,000	5,000	5,000	5,000	5,000	5,000	5,000
R ²	0.0949	0.2299	0.1754	0.0928	0.1136	0.2698	0.1590	0.0928
Adjusted R ²	0.0938	0.2290	0.1744	0.0917	0.1126	0.2690	0.1580	0.0917
Residual Std. Error	0.1372	0.0453	0.1318	0.1015	0.1284	0.0376	0.1412	0.1015
F Statistic	87.2102***	248.4029***	176.9566***	85.1020***	106.6782***	307.5279***	157.3473***	85.1020***

Note: Entries are the regression coefficients and t-statistics within parenthesis. Results are derived from the regression: $ADCC_t = \beta_0 + \beta_1 EPU_t + \beta_2 GPR_t + \beta_3 VIX_t + \beta_4 REC_t + \beta_5 TERM_t + \beta_6 SPREAD_t + \varepsilon_t$ where ADCC is the conditional correlation between gold returns and oil returns or the given shock type. EPU, GPR, VIX are the uncertainty indexes and TERM and SPREAD are the term premium and the credit spread. REC is a dummy variable which takes the value of 1 during recessionary periods and zero otherwise. *p<0.1; **p<0.05; ***p<0.01

We can see very similar results regardless of the distribution assumption of the residuals. Indicating that the innovation's distribution is not too far from normal. Basher and Sadorsky (2016) studied the hedge ratio forecast performance of different GARCH models and showed that the models performed very similarly regardless of the distribution assumption. Furthermore, Mensi et al. (2016) compared the forecast performance of a DCC-FIAPARCH model with different residual distribution assumptions. They found that the best-performing model was with a skewed Student's t error distribution, but the other models also performed similarly.

On the basis of the very similar results, we can conclude that the model is robust against the error distribution assumption.

VI.6. Comparison with Baumeister and Hamilton (2019)

A different approach to separate oil price shocks was presented by Baumeister and Hamilton (2019), which methodology appeared in the study of Oliyide et al. (2021) and Salisu and Adediran (2020). Baumeister and Hamilton (2019) argue with the strict assumptions of the other SVAR models, which are used to separate different oil price shocks. Their model is based on a less strict Bayesian inference methodology, which allows to separate four different shock types: supply shocks (SS), consumption demand shocks (CDS), inventory demand shocks (IDS) and economic activity shocks (EAS). The shock series were obtained from the authors' website (sites.google.com/site/cjsbaumeister/datasets).

Table 23: Comparison with Baumeister and Hamilton (2019)

	ADCC Ready (2018)				ADCC Baumeister and Hamilton (2019)			
	oil	SS	DS	RS	SS	CDS	IDS	EAS
Constant	0.3093*** (0.0361)	0.0743*** (0.0131)	0.4739*** (0.0340)	-0.1109*** (0.0264)	-0.1402*** (0.0126)	0.0647*** (0.0085)	0.1464*** (0.0092)	0.0267*** (0.0070)
EPU	-0.0007*** (0.0001)	-0.0001 (0.0001)	-0.0010*** (0.0001)	0.0002** (0.0001)	0.0001 (0.00005)	-0.0004*** (0.00003)	0.0004*** (0.00004)	-0.0003*** (0.00003)
GPR	-0.0006** (0.0003)	0.00003 (0.0001)	-0.0011*** (0.0002)	0.0009*** (0.0002)	-0.0001 (0.0001)	-0.00002 (0.0001)	-0.0002*** (0.0001)	0.0001 (0.0001)
VIX	0.0032*** (0.0011)	0.0023*** (0.0004)	-0.00004 (0.0010)	-0.0002 (0.0008)	0.0009** (0.0004)	0.0024*** (0.0003)	-0.0023*** (0.0003)	0.0010*** (0.0002)
Observations	238	238	238	238	238	238	238	238
R ²	0.1122	0.1358	0.2753	0.1026	0.0625	0.4018	0.4392	0.3641
Adjusted R ²	0.1008	0.1247	0.2660	0.0911	0.0505	0.3941	0.4320	0.3559
Residual Std. Error	0.1290	0.0467	0.1214	0.0943	0.0451	0.0302	0.0331	0.0252
F Statistic	9.8598***	12.2518***	29.6333***	8.9191***	5.1993***	52.3884***	61.0937***	44.6570***

Note: Entries are the regression coefficients and t-statistics within parenthesis. Results are derived from the regression: $ADCC_t = \beta_0 + \beta_1 EPU_t + \beta_2 GPR_t + \beta_3 VIX_t + \varepsilon_t$ where ADCC is the conditional correlation between gold returns and oil returns or the given shock type. EPU, GPR, VIX are the uncertainty indexes. *p<0.1; **p<0.05; ***p<0.01

This methodology allows to separate shock types on a monthly basis, which is less ideal compared to the daily, as shown earlier. We can see that the separated shocks based on this methodology are generally more affected by the uncertainty indexes. This is most likely because uncertainty indexes have the strongest effect on demand shocks and their model further distinguishes between inventory and consumption demand shocks.

VIX has a positive effect on supply shocks regardless of the model, while there is a difference between demand shocks. Oliyide et al. (2021) also highlighted this effect, shock types separated this manner are more affected by the EPU and provided evidence that there is a causal effect both in conditional mean and conditional variance.

These results highlight the importance of the shock separation model and could explain the different results in the literature. Since the shock separations are based on very different methodologies, they are not really comparable. However, uncertainty indexes affect connectedness regardless of the model, which further supports that uncertainty has a strong impact in the nexus.

VII. Conclusion

Motivated by previous research indicating a significant effect of uncertainty in the oil-gold nexus, the major objective of the study was to examine the effect of uncertainty on the oil-gold connectedness. In the study, changes in oil price were separated into structural shocks and I modeled their correlations with the ADCC-GARCH methodology. I examined the effect of uncertainty on the correlation with several models, including linear and nonlinear ones. I also tested the impact of OPEC and FOMC announcements and the COVID-19 pandemic. Hedging implications and considerations in asset allocation were provided.

The findings show that separating oil price changes into structural oil price shocks is an important aspect. The different types of shocks have different connections with gold returns, providing further insight into the oil-gold nexus.

Uncertainty plays an important role in the correlation among the assets. Generally speaking, uncertainty affects the oil-gold and demand shock-gold connectedness negatively, while the supply- and risk shock-gold connectedness positively. Investors should consider the underlying source of the oil price shock and the uncertainty against which they want to protect their portfolio.

The effect of uncertainty is regime-dependent, during certain periods it has a more pronounced impact, linear models are unable to capture this effect. It is important to consider the regime dependency in the context, during certain times the uncertainty measures can have the opposite impact. Conclusions and implications derived from linear models can be misleading and can provide unreliable results.

Gold cannot be considered as neither a hedge nor a safe haven against the risks of the oil market during highly uncertain periods. Unlike against stock market risk, investors should look elsewhere to hedge and protect their investments efficiently. Gold can be considered as a diversifier asset and might have increasing benefits during certain types of uncertainty, but the optimal hedge is rather costly to construct.

The OPEC announcements affect the nexus and failing to agree has the most significant positive impact. OPEC is responsible for a great portion of oil exports, when the members fail to agree, an oil market-related uncertainty is introduced to the market, driving the connection between oil and gold stronger.

The FOMC announcements also affect the nexus. Based on the direction of the change in the target rate the announcements have different impact. The decision to decrease and if the rate left unchanged has the most significant effect.

The recent COVID-19 pandemic had a significant negative impact on the connection. Pandemics and other unforeseen events can have a great impact on asset connections, during which

gold prices tend to rise and might be able to diversify more risk away than at normal times. For this reason, gold in an oil portfolio can be useful for providing loss absorption when catastrophic events occur.

Other aspects can be mentioned, the daily shock separation might be favorable compared to the monthly and the different uncertainty measures have different but usually significant impact. Other variables which describe the general state of the economy, are also important to examine. The effect seems to be symmetric, the impact of uncertainty does not depend on the sign of the oil returns or shocks. Supply shocks are more affected by the actual geopolitical events, while demand shocks and oil returns respond significantly to perceived geopolitical risks.

The main advantage and contribution of the study is the consideration of several aspects, which were highlighted by previous works. The separation of oil price shocks, the use of both linear and nonlinear models and the different uncertainty measures. Furthermore, no previous research considered the effect of OPEC and FOMC announcements in the same context. Similar studies either considered only the role of separated shocks or the effect of uncertainty on oil-gold connectedness, but none of them considered both of these aspects in the same time.

For following research, an important consideration can be other precious metals or cryptocurrencies in the same context. In addition to that, using the methodology of Baumeister and Hamilton (2019) might provide some additional information about the nexus. Another extension can be made by using spillover models to examine the risk transmissions among the series in the presence of uncertainty.

VIII. References

- Abdullah, A., & Bakar, M. J. A. (2015). The application of gold price, interest rates and inflation expectations in capital markets. *International Journal of Economics and Finance*, 7(2), 293-302.
- Akhtaruzzaman, M., Boubaker, S., Lucey, B. M., & Sensoy, A. (2021). Is gold a hedge or a safe-haven asset in the COVID-19 crisis?. *Economic Modelling*, 102, 105588.
- Albulescu, C. T., Demirer, R., Raheem, I. D., & Tiwari, A. K. (2019). Does the US economic policy uncertainty connect financial markets? Evidence from oil and commodity currencies. *Energy Economics*, 83, 375-388.
- Ali, M., Alam, N., & Rizvi, S. A. R. (2020). Coronavirus (COVID-19)—An epidemic or pandemic for financial markets. *Journal of Behavioral and Experimental Finance*, 27, 100341.
- Antonakakis, N., Gupta, R., Kollias, C., & Papadamou, S. (2017). Geopolitical risks and the oil-stock nexus over 1899–2016. *Finance Research Letters*, 23, 165-173.
- Askari, H., & Krichene, N. (2010). An oil demand and supply model incorporating monetary policy. *Energy*, 35(5), 2013-2021.
- Atems, B., Kapper, D., & Lam, E. (2015). Do exchange rates respond asymmetrically to shocks in the crude oil market?. *Energy Economics*, 49, 227-238.
- Badshah, I., Demirer, R., & Suleman, M. T. (2019). The effect of economic policy uncertainty on stock-commodity correlations and its implications on optimal hedging. *Energy Economics*, 84, 104553.
- Baker, S. R., Bloom, N., & Davis, S. J. (2016). Measuring economic policy uncertainty. *The quarterly journal of economics*, 131(4), 1593-1636.
- Balcilar, M., Gupta, R., & Pierdzioch, C. (2016). Does uncertainty move the gold price? New evidence from a nonparametric causality-in-quantiles test. *Resources Policy*, 49, 74-80.
- Basher, S. A., & Sadorsky, P. (2016). Hedging emerging market stock prices with oil, gold, VIX, and bonds: A comparison between DCC, ADCC and GO-GARCH. *Energy Economics*, 54, 235-247.
- Baumeister, C., & Hamilton, J. D. (2019). Structural interpretation of vector autoregressions with incomplete identification: Revisiting the role of oil supply and demand shocks. *American Economic Review*, 109(5), 1873-1910.
- Baur, D. G., & Lucey, B. M. (2010). Is gold a hedge or a safe haven? An analysis of stocks, bonds and gold. *Financial Review*, 45(2), 217-229.

- Baur, D. G., & McDermott, T. K. (2010). Is gold a safe haven? International evidence. *Journal of Banking & Finance*, 34(8), 1886-1898.
- Baur, D. G., & Smales, L. A. (2020). Hedging geopolitical risk with precious metals. *Journal of Banking & Finance*, 117, 105823.
- Beckmann, J., Berger, T., & Czudaj, R. (2019). Gold price dynamics and the role of uncertainty. *Quantitative Finance*, 19(4), 663-681.
- Bekaert, G., Engstrom, E. C., & Xu, N. R. (2021). The time variation in risk appetite and uncertainty. *Management Science*.
- Bessembinder, H., & Chan, K. (1992). Time-varying risk premia and forecastable returns in futures markets. *Journal of Financial Economics*, 32(2), 169-193.
- Bodilsen, S., Eriksen, J. N., & Grønberg, N. S. (2021). Asset pricing and FOMC press conferences. *Journal of Banking & Finance*, 128, 106163.
- Bouoiyour, J., Selmi, R., Hammoudeh, S., & Wohar, M. E. (2019). What are the categories of geopolitical risks that could drive oil prices higher? Acts or threats?. *Energy Economics*, 84, 104523.
- Bouri, E., Molnár, P., Azzi, G., Roubaud, D., & Hagfors, L. I. (2017). On the hedge and safe haven properties of Bitcoin: Is it really more than a diversifier?. *Finance Research Letters*, 20, 192-198.
- Broock, W. A., Scheinkman, J. A., Dechert, W. D., & LeBaron, B. (1996). A test for independence based on the correlation dimension. *Econometric reviews*, 15(3), 197-235.
- Caldara, D., & Iacoviello, M. (2018). Measuring geopolitical risk. FRB International Finance Discussion Paper, (1222).
- Caldara, D., Iacoviello, M., Mollogo, P., Prestipino, A., & Raffo, A. (2020). The economic effects of trade policy uncertainty. *Journal of Monetary Economics*, 109, 38-59.
- Cappiello, L., Engle, R. F., & Sheppard, K. (2006). Asymmetric dynamics in the correlations of global equity and bond returns. *Journal of Financial econometrics*, 4(4), 537-572.
- Cboe Exchange (2021). Cboe Volatility Index. White Paper
available: cdn.cboe.com/resources/vix/vixwhite.pdf
- Charlot, P., & Marimoutou, V. (2014). On the relationship between the prices of oil and the precious metals: Revisiting with a multivariate regime-switching decision tree. *Energy Economics*, 44, 456-467.
- Chebbi, T. (2021). The response of precious metal futures markets to unconventional monetary surprises in the presence of uncertainty. *International Journal of Finance & Economics*, 26(2),

1897-1916.

Cieslak, A., & Pang, H. (2021). Common shocks in stocks and bonds. *Journal of Financial Economics*, 142(2), 880-904.

Clements, A., Shield, C., & Thiele, S. (2019). Which oil shocks really matter in equity markets?. *Energy Economics*, 81, 134-141.

Das, D., Kannadhasan, M., & Bhowmik, P. (2019). Geopolitical risk and precious metals. *Journal of Economic Research*, 24(1), 49-66.

Das, D., Le Roux, C. L., Jana, R. K., & Dutta, A. (2020). Does Bitcoin hedge crude oil implied volatility and structural shocks? A comparison with gold, commodity and the US Dollar. *Finance Research Letters*, 36, 101335.

Degiannakis, S., Filis, G., & Panagiotakopoulou, S. (2018). Oil price shocks and uncertainty: How stable is their relationship over time?. *Economic Modelling*, 72, 42-53.

Demirer, R., Gupta, R., Pierdzioch, C., & Shahzad, S. J. H. (2020). The predictive power of oil price shocks on realized volatility of oil: A note. *Resources policy*, 69, 101856.

Demirer, R., & Kutan, A. M. (2010). The behavior of crude oil spot and futures prices around OPEC and SPR announcements: An event study perspective. *Energy Economics*, 32(6), 1467-1476.

Dutta, A., Das, D., Jana, R. K., & Vo, X. V. (2020). COVID-19 and oil market crash: Revisiting the safe haven property of gold and Bitcoin. *Resources Policy*, 69, 101816.

Engle, R. (2002). Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroskedasticity models. *Journal of Business & Economic Statistics*, 20(3), 339-350.

Fakhfekh, M., Jeribi, A., Ghorbel, A., & Hachicha, N. (2021). Hedging stock market prices with WTI, Gold, VIX and cryptocurrencies: A comparison between DCC, ADCC and GO-GARCH models. *International Journal of Emerging Markets*.

Fasanya, I. O., Adekoya, O. B., & Adetokunbo, A. M. (2021). On the connection between oil and global foreign exchange markets: The role of economic policy uncertainty. *Resources Policy*, 72, 102110.

Filis, G., Degiannakis, S., & Floros, C. (2011). Dynamic correlation between stock market and oil prices: The case of oil-importing and oil-exporting countries. *International review of financial analysis*, 20(3), 152-164.

Gu, X., Zhu, Z., & Yu, M. (2021). The macro effects of GPR and EPU indexes over the global oil market—Are the two types of uncertainty shock alike?. *Energy Economics*, 100, 105394.

- Hammoudeh, S., & Yuan, Y. (2008). Metal volatility in presence of oil and interest rate shocks. *Energy Economics*, 30(2), 606-620.
- Husted, L., Rogers, J., & Sun, B. (2020). Monetary policy uncertainty. *Journal of Monetary Economics*, 115, 20-36.
- Jang, H., & Seo, B. K. (2020). Monetary policy rate expectation and energy prices during the FOMC announcement period. *Finance Research Letters*, 32, 101093.
- Joëts, M., Mignon, V., & Razafindrabe, T. (2017). Does the volatility of commodity prices reflect macroeconomic uncertainty?. *Energy Economics*, 68, 313-326.
- Jurado, K., Ludvigson, S. C., & Ng, S. (2015). Measuring uncertainty. *American Economic Review*, 105(3), 1177-1216.
- Kang, S. H., McIver, R., & Yoon, S. M. (2017). Dynamic spillover effects among crude oil, precious metal, and agricultural commodity futures markets. *Energy Economics*, 62, 19-32.
- Kang, W., Ratti, R. A., & Vespignani, J. L. (2017). Oil price shocks and policy uncertainty: New evidence on the effects of US and non-US oil production. *Energy Economics*, 66, 536-546.
- Kilian, L. (2009). Not all oil price shocks are alike: Disentangling demand and supply shocks in the crude oil market. *American Economic Review*, 99(3), 1053-69.
- Kilian, L., & Park, C. (2009). The impact of oil price shocks on the US stock market. *International Economic Review*, 50(4), 1267-1287.
- Klar, B., Lindner, F., & Meintanis, S. G. (2012). Specification tests for the error distribution in GARCH models. *Computational Statistics & Data Analysis*, 56(11), 3587-3598.
- Klein, T. (2018). Trends and contagion in WTI and Brent crude oil spot and futures markets-The role of OPEC in the last decade. *Energy Economics*, 75, 636-646.
- Koenker, R., & Bassett Jr, G. (1978). Regression quantiles. *Econometrica: journal of the Econometric Society*, 33-50.
- Koenker, R., Ng, P., & Portnoy, S. (1994). Quantile smoothing splines. *Biometrika*, 81(4), 673-680.
- Kroner, K. F., & Ng, V. K. (1998). Modeling asymmetric comovements of asset returns. *The review of financial studies*, 11(4), 817-844.
- Kroner, K. F., & Sultan, J. (1993). Time-varying distributions and dynamic hedging with foreign currency futures. *Journal of financial and quantitative analysis*, 28(4), 535-551.
- Ku, Y. H. H., Chen, H. C., & Chen, K. H. (2007). On the application of the dynamic conditional correlation model in estimating optimal time-varying hedge ratios. *Applied Economics Letters*,

14(7), 503-509.

Lescaroux, F. (2009). On the excess co-movement of commodity prices—a note about the role of fundamental factors in short-run dynamics. *Energy Policy*, 37(10), 3906-3913.

Li, X., Liang, C., Chen, Z., & Umar, M. (2022). Forecasting crude oil volatility with uncertainty indicators: New evidence. *Energy Economics*, 108, 105936.

Li, Y., Huang, J., Gao, W., & Zhang, H. (2021). Analyzing the time-frequency connectedness among oil, gold prices and BRICS geopolitical risks. *Resources Policy*, 73, 102134.

Lin, S. X., & Tamvakis, M. (2010). OPEC announcements and their effects on crude oil prices. *Energy Policy*, 38(2), 1010-1016.

Liu, Y., Han, L., & Xu, Y. (2021). The impact of geopolitical uncertainty on energy volatility. *International Review of Financial Analysis*, 75, 101743.

Loutia, A., Mellios, C., & Andriosopoulos, K. (2016). Do OPEC announcements influence oil prices?. *Energy Policy*, 90, 262-272.

Lyu, Y., Wang, P., Wei, Y., & Ke, R. (2017). Forecasting the VaR of crude oil market: do alternative distributions help?. *Energy Economics*, 66, 523-534.

Marfatia, H. A., Gupta, R., & Cakan, E. (2021). Dynamic impact of the US monetary policy on oil market returns and volatility. *The Quarterly Review of Economics and Finance*, 80, 159-169.

Melvin, M., & Sultan, J. (1990). South African political unrest, oil prices, and the time varying risk premium in the gold futures market. *The Journal of Futures Markets* (1986-1998), 10(2), 103.

Mensi, W., Hammoudeh, S., Nguyen, D. K., & Kang, S. H. (2016). Global financial crisis and spillover effects among the US and BRICS stock markets. *International Review of Economics & Finance*, 42, 257-276.

Mensi, W., Nekhili, R., Vo, X. V., & Kang, S. H. (2021). Oil and precious metals: Volatility transmission, hedging, and safe haven analysis from the Asian crisis to the COVID-19 crisis. *Economic Analysis and Policy*, 71, 73-96.

Mokni, K., Ajmi, A. N., Bouri, E., & Vo, X. V. (2020). Economic policy uncertainty and the Bitcoin-US stock nexus. *Journal of Multinational Financial Management*, 57, 100656.

Mokni, K., Al-Shboul, M., & Assaf, A. (2021). Economic policy uncertainty and dynamic spillover among precious metals under market conditions: Does COVID-19 have any effects?. *Resources Policy*, 74, 102238.

Mokni, K., Hammoudeh, S., Ajmi, A. N., & Youssef, M. (2020). Does economic policy uncer-

tainty drive the dynamic connectedness between oil price shocks and gold price?. *Resources Policy*, 69, 101819.

Narayan, P. K., Narayan, S., & Zheng, X. (2010). Gold and oil futures markets: Are markets efficient?. *Applied energy*, 87(10), 3299-3303.

Nusair, S. A., & Olson, D. (2019). The effects of oil price shocks on Asian exchange rates: Evidence from quantile regression analysis. *Energy Economics*, 78, 44-63.

Oliyide, J. A., Adekoya, O. B., & Khan, M. A. (2021). Economic policy uncertainty and the volatility connectedness between oil shocks and metal market: An extension. *International Economics*, 167, 136-150.

Pástor, Ľ., & Veronesi, P. (2013). Political uncertainty and risk premia. *Journal of financial Economics*, 110(3), 520-545.

Pindyck, R. S., & Rotemberg, J. J. (1988). The excess co-movement of commodity prices.

Ratner, M., & Chiu, C. C. J. (2013). Hedging stock sector risk with credit default swaps. *International Review of Financial Analysis*, 30, 18-25.

Ready, R. C. (2018). Oil prices and the stock market. *Review of Finance*, 22(1), 155-176.

Reboredo, J. C. (2013). Is gold a hedge or safe haven against oil price movements?. *Resources Policy*, 38(2), 130-137.

Reboredo, J. C., & Uddin, G. S. (2016). Do financial stress and policy uncertainty have an impact on the energy and metals markets? A quantile regression approach. *International Review of Economics & Finance*, 43, 284-298.

Rehman, M. U., Shahzad, S. J. H., Uddin, G. S., & Hedström, A. (2018). Precious metal returns and oil shocks: A time varying connectedness approach. *Resources Policy*, 58, 77-89.

Rosa, C. (2014). The high-frequency response of energy prices to US monetary policy: Understanding the empirical evidence. *Energy Economics*, 45, 295-303.

Salisu, A. A., & Adediran, I. (2020). Gold as a hedge against oil shocks: evidence from new datasets for oil shocks. *Resources Policy*, 66, 101606.

Salisu, A. A., Vo, X. V., & Lawal, A. (2021). Hedging oil price risk with gold during COVID-19 pandemic. *Resources Policy*, 70, 101897.

Sari, R., Hammoudeh, S., & Soytas, U. (2010). Dynamics of oil price, precious metal prices, and exchange rate. *Energy Economics*, 32(2), 351-362.

Schmidbauer, H., & Röscher, A. (2012). OPEC news announcements: Effects on oil price expectation and volatility. *Energy Economics*, 34(5), 1656-1663.

Sharif, A., Aloui, C., & Yarovaya, L. (2020). COVID-19 pandemic, oil prices, stock market, geopolitical risk and policy uncertainty nexus in the US economy: Fresh evidence from the wavelet-based approach. *International Review of Financial Analysis*, 70, 101496.

Smales, L. A. (2021). Geopolitical risk and volatility spillovers in oil and stock markets. *The Quarterly Review of Economics and Finance*, 80, 358-366.

Spencer, S., & Bredin, D. (2019). Agreement matters: OPEC announcement effects on WTI term structure. *Energy Economics*, 80, 589-609.

Tiwari, A. K., Aye, G. C., Gupta, R., & Gkillas, K. (2020). Gold-oil dependence dynamics and the role of geopolitical risks: Evidence from a Markov-switching time-varying copula model. *Energy Economics*, 88, 104748.

Tiwari, A. K., & Sahadudheen, I. (2015). Understanding the nexus between oil and gold. *Resources Policy*, 46, 85-91.

Turhan, M. I., Sensoy, A., Ozturk, K., & Hacihasanoglu, E. (2014). A view to the long-run dynamic relationship between crude oil and the major asset classes. *International Review of Economics & Finance*, 33, 286-299.

Uddin, G. S., Rahman, M. L., Shahzad, S. J. H., & Rehman, M. U. (2018). Supply and demand driven oil price changes and their non-linear impact on precious metal returns: A Markov regime switching approach. *Energy Economics*, 73, 108-121.

Wang, G. J., Ma, X. Y., & Wu, H. Y. (2020). Are stablecoins truly diversifiers, hedges, or safe havens against traditional cryptocurrencies as their name suggests?. *Research in International Business and Finance*, 54, 101225.

WHO (2020). COVID 19 Public Health Emergency of International Concern (PHEIC)

available: www.who.int/docs/default-source/coronaviruse/global-research-and-innovation-forum-towards-a-research-roadmap.pdf?sfvrsn=a7fdb05b_1&download=true

Wu, S., Tong, M., Yang, Z., & Derbali, A. (2019). Does gold or Bitcoin hedge economic policy uncertainty?. *Finance Research Letters*, 31, 171-178.

Ye, W., Zhu, Y., Wu, Y., & Miao, B. (2016). Markov regime-switching quantile regression models and financial contagion detection. *Insurance: Mathematics and Economics*, 67, 21-26.

Youssef, M., & Mokni, K. (2021). Oil-gold nexus: Evidence from regime switching-quantile regression approach. *Resources Policy*, 73, 102215.

Zhang, Y. J., & Wei, Y. M. (2010). The crude oil market and the gold market: Evidence for cointegration, causality and price discovery. *Resources Policy*, 35(3), 168-177.