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Aviral Kumar Tiwari
Montpellier Business School
Goodness C. Aye
University of Pretoria
Rangan Gupta
University of Pretoria
Konstantinos Gkillas
University of Patras
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Department of Economics
University of Pretoria
0002, Pretoria
South Africa
Tel: +27 12 420 2413

Gold-Oil Dependence Dynamics and the Role of Geopolitical Risks: Evidence from a Markov-Switching Time-Varying Copula Model

Aviral Kumar Tiwari[*], Goodness C. Aye[**], Rangan Gupta[***] and Konstantinos Gkillas[****]

Abstract

This paper examined the dependence structure and dynamics between gold and oil prices. Specifically, we examined the hedge and safe haven ability of gold for oil prices using the time-varying Markov switching copula models and daily gold prices and West Texas Intermediate Institute (WTI) crude oil spot prices from 2 January 1985 to 30 November 2017. The heterogeneity of market agents is captured by decomposing the raw original series into different multi-resolution analysis (MRA) investment horizons (D1-S9). Further, we examined the effect of geopolitical risks on the dynamic dependence between gold and oil. We provide evidence of time-varying Markov tail dependence structure and dynamics between gold and oil. While our results showed that gold is a good hedge for oil returns and for short- and medium-term investors, it cannot protect long-term investors against losses arising from increasing oil prices. We also provide evidence in support of the safe haven ability of gold for oil. Further, we show that the inclusion of geopolitical risks in a pure gold and oil asset portfolio provides diversification benefits since the former has mostly negative effect on the dependence structure between gold and oil.

Keywords: Time-Varying Dependence, Gold and Oil Markets, Copula Models, Geopolitical Risks.

JEL Codes: C22, Q02.

[*] Montpellier Business School, 2300, Avenue des Moulins, 34185, Montpellier Cedex 4 0002, France. Email: a.tiwari@montpellier-bs.com.

[**] Corresponding author. Department of Economics, University of Pretoria, Pretoria, 0002, South Africa. Email: goodness.aye@gmail.com.

[***] Department of Economics, University of Pretoria, Pretoria, 0002, South Africa. Email: rangan.gupta.@up.ac.za.

[****] Department of Business Administration , University of Patras, University Campus, Rio, P.O. Box 1391, 26500 Patras, Greece. Email: gillask@upatras.gr.

1. Introduction

Gold and oil are major global commodities whose demand is usually very high given their role in both production and consumption. Both are liquid and as such very widely traded.[1] Given these roles, movements in gold and oil prices are of great concern to economic agents since these have implications for both the real economy and financial markets. Whether these two commodities move together or not, on average and/or in times of market crisis is a question that needs to be answered. This forms the basis of this study. The answer to this question will provide evidence of the hedge or safe haven ability of gold respectively against oil price movement. Moreover, of interest is whether the relationship varies across different states. Understanding these have implications for investors' diversification portfolio decision and hedging as well as policy design. An asset is a hedge if it is uncorrelated or negatively correlated with another asset or portfolio on average while it is a safe haven if it is uncorrelated or negatively correlated with another asset or portfolio in times of market crisis (Baur and Lucey, 2010; Baur and McDermott, 2010).

The relationship between gold and oil prices can explained implicitly by the studies that examined the hedging or safe haven role of gold against inflation, stock or bond markets and the US dollar exchange rate. This is because a change in the price of oil leads to changes in these variables, which have consequence for gold prices. For example, an increase in oil prices can trigger rising general price level thus increasing the price of gold as well, thereby making gold a possible hedge against inflation (Chua and Woodward, 1982; Ghosh et al., 2004; Worthington and Pahlavani, 2007; Tully and Lucy, 2007; Blose; 2010; Aye et al. 2016, 2017 etc). Also higher oil prices can impact negatively on economic growth and asset prices thus causing investors to turn to alternative portfolios such as gold (Baur and McDermott, 2010; Baur and Lucey, 2010; Reboredo, 2010). Further, a depreciation of the US dollar against major world currencies can result in investors increasing their investment in gold as a safe haven, which consequently increases the price of gold. A similar behaviour is seen in the oil price when the U.S dollar depreciates (Capie, et al., 2005; Joy, 2011; Reboredo, 2012).

Explicitly, there are some empirical studies that have examined the relationship between gold and oil prices (Baffes, 2007; Hammoudeh and Yuan, 2008; Soytas et al., 2009; Sari et al., 2010; Narayan et al., 2010; Zhang and Wei, 2010; Tiwari and Sahadudheen, 2015). However, these studies did not consider the role of gold as a hedge or safe haven against oil prices. Few studies examined the hedging or safe haven role of gold against oil prices. For example, the study by Balcilar et al. (2018) examined the causal links between oil and gold using time□varying causality tests and found that there is strong time-varying causal links between oil and gold. The study therefore warned that the assumption of non-causality between oil and gold might lead to danger in using gold as a hedge instrument against the oil price risk. Reboredo (2013) investigated whether gold acts as a hedge and safe haven against oil price using copulas approach. The results provide evidence against hedging ability of gold for oil but support its safe haven role. Although Reboredo (2013) analysed the dependence structure between oil and gold, the study did not give information about the existence of regime change in the dependence. In our paper, we propose a novel regime switching copula model that allows for regime change in the copula parameter in order to assess the time-varying dependence structure between gold and oil prices. The main advantage of this model is that it does not require an ad hoc determination of change point in the dependence structure (da Silva Filho, et al., 2012; Boubaker and Sghaier, 2016). Moreover, we contribute to the literature on oil and gold relationship by not only examining this for the original return series but also for the decomposed multi-resolution analysis (MRA) wavelet scales, D1-S9. This decomposition is motivated by the heterogeneous market hypothesis, which categorizes traders in terms of their

[1] The specific roles of gold can be found in Aye et al. (2016, 2017).

time horizons or level scales. This is important as market participants may differ in terms of expectations, risk profiles, beliefs, information sets among others (Mensi et al., 2016). This will provide new insight into the reactions of short-, medium- and long-term investors in terms of gold and oil dependence.

Further, if gold is a safe-haven for oil prices, one would ideally expect the correlation between gold and oil to be negatively impacted by crisis situations. This assumption stems from the fact that empirical evidence has shown that economic agents and markets react to exogenous anthropogenic, natural and/or political events (Kaplanski and Levi, 2010, Pástor and Veronesi, 2013). For instance, it has been shown that events such as elections, civil strife, government changes, terrorist attacks, geopolitical friction and tension could affect economic performance and asset markets directly, but also the cross correlation of assets, investor sentiments, portfolio allocation and diversification decisions (Asteriou and Siriopoulos, 2003, Drakos and Kallandranis, 2015, Omar et al., 2016, Antonakakis et al., 2017). Therefore, this study contributes to the literature on the oil-gold dependence dynamics by evaluating the influence of geopolitical risks (GPR) on the correlation between gold and oil prices. To this effect, we estimated a regression model using dependence parameter estimates from the best copula models for both the return and wavelet series. This sort of analysis is particularly important in our context given that oil is a strategic commodity that has its large share produced in geopolitically volatile and unstable regions such as the Middle East, West and North Africa. The analysis of the influence of geopolitical risks, (i.e., non-financial factors) on the dependence structure of oil fills a gap in the growing empirical literature on safe haven assets as most studies focus on gold's safe haven status relative to financial variables such as stocks, bonds, currencies and oil as discussed above (Baur and Smales, 2018).

The remainder of the paper is organized as follows: Section 2 outlines the copula models, while Section 3 discusses the data, Section 4 presents the results, with Section 4 concluding the paper.

2. Methodology

The role of gold as a hedge or safe haven against oil prices is examined using the dynamic dependence structure between oil and gold. Specifically, the study uses a Markov switching time-varying copula to measure the dynamic dependence structure between oil and gold.

2.1 Bivariate Copulas

A copula is a function that allows the joining of several univariate distributions to form a valid multivariate distribution with no loss of information from the original multivariate distribution. According to Schweizer and Sklar (1983) and da Silva Filho et al. (2012), an n-dimensional copula $C(u_1,...,u_n)$ is a multivariate distribution function in $[0,1]^n$ whose marginal distributions are uniform in the $[0,1]$ interval. For any joint distribution $H(x_1,...,x_n)$ with marginals $F_1(x_1),...,F_n(x_n)$, we have $H(x_1,...,x_n) = C(F_1(x_1),...,F_n(x_n))$. (1)

If $F_1,...,F_n$, are continuous, then the copula C associated to H is unique and may be obtained by $C(u_1,...,u_n) = H(F_1^{(-1)}(u_1),...,F_n^{(-1)}(u_n))$, (2)

where $u_1 = F_1(x_1),...,u_n = F_n(x_n)$.

One can easily obtain the density function related to the joint distribution in (1) since $F_1,...,F_n$ and C are n-differentiable. Thus, in a bivariate case, the density function is given by

$$h(x_1, x_2) = c(F_1(x_1), F_2(x_2))\prod_{i=1}^{2} f_i(x_i), \quad (3)$$

where h is the density function associated with H, f_i is the density function for each marginal, and the copula density c is obtained by differentiating (1), which can be written as

$$c(F_1(x_1),...,F_n(x_n)) = \frac{h(F_1^{(-1)}(u_1), F_2^{(-1)}(u_2))}{\prod_{i=1}^{2} f_i(F_i^{(-1)}(u_i)}. \tag{4}$$

The copula functions often used in finance have elliptical forms because they are associated with a quadratic form of correlation between the marginal (da Silva Filho et al., 2012). Examples are the Gaussian (Normal) and Student-t copulas. The dependence structure related to this copula family is the linear correlation coefficient, which belongs to the $[-1, 1]$ interval. Indeed, distribution functions from this family are symmetric.

The Archimedean and Gumbel (1960) copulas have also been used. Archimedean copula function may have a dependence measure belonging to the most diverse ranges of variation, depending on the functional form of the generating factor. The Gumbel copula has mostly been used in Extreme Value Theory (EVT) and allows only positive (upper tail) dependence structures. Gumbel parameter belongs to the interval $[1, +\infty]$. Due to the diversity of copula functions with specific dependence structures, it becomes impossible to compare different copula functional forms. However, focusing on a dependence measure known as tail dependence makes the comparison possible. We provide the definition of tail dependence in what follows.

Definition 1. If the limit D $\lim_{\varepsilon\to 0} \Pr[U_1 \le \varepsilon | U_2 \le \varepsilon] = \lim_{\varepsilon\to 0} \Pr[U_2 \le \varepsilon | U_1 \le \varepsilon] = \lim_{\varepsilon\to 0} C(\varepsilon,\varepsilon)/\varepsilon = \tau^L$ exists, then copula C has a lower tail dependence if $\tau^L \in [0, 1]$. Otherwise, C has no lower tail dependence.

If the limit $\lim_{\delta\to 1} \Pr[U_1 > \delta | U_2 > \delta] = \lim_{\delta\to 1} \Pr[U_2 > \delta | U_1 > \delta] = \lim_{\delta\to 1^-} (1 - 2\delta + C(\delta,\delta))/1-\delta) = \tau^U$ exists, then copula C has upper tail dependence if $\tau^U \in [0, 1]]$. Otherwise, C has no upper tail dependence.

Using tail dependence measures allow us to determine the model that best reproduces empirical or stylized facts, about commodity markets. Also, the tail dependence measure can be thought of as the probability that an extreme event occurs in a market, given that this event is occurring in another market. In addition, tail dependence is fully defined by the dependence structure (that is, the related copula), and is not affected by marginal distribution variations. Several functional forms that can be used as copulas. Nelsen (2006) provided some examples of copula families and a guide for their construction. In this study, five copula functions are tested[2]. Table 1 summarizes the characteristics of the copula functions used. These are:

Gumbel copula: This has only upper tail dependence and is given as

$$C_G(u_1, u_2 | \theta) = \exp\left(-\left((-\log u_1)^\theta + (-\log u_2)^\theta\right)^{1/\theta}\right), \quad \theta \in [1, +\infty].$$

Rotated Gumbel copula: This has only lower tail dependence and is specified as

$$C_{RG}(u_1, u_2 | \theta) = u_1 + u_2 - 1 + C_G(1-u_1, 1-u_2 | \theta) \quad \theta \in [1, +\infty].$$

Symmetrized Joe–Clayton copula: This is specified as

[2] We draw only bivariate copula functions since our work focuses on this dimension.

$$C_{SJC}(u_1,u_2|\tau^U,\tau^L) = 0.5\cdot(C_{JC}(u_1,u_2|\tau^U,\tau^L) + C_{JC}(1-u_1,1-u_2|\tau^U,\tau^L) + u_1 + u_2 - 1),$$

where C_{JC} is the Joe–Clayton copula, also called "$BB7$", given by

$$C_{JC}(u_1,u_2|\tau^U,\tau^L) = 1-\left(1-\left\{\left[1-(1-u_1)^{\kappa}\right]^{-\gamma} + \left[1-(1-u_2)^{\kappa}\right]^{-\gamma} - 1\right\}^{-1/\gamma}\right)^{-1/\kappa}, \quad \text{with}$$

$\kappa = 1/\log_2(2-\tau^U)$,

$\gamma = 1/\log_2(\tau^L)$, and $\tau^U, \tau^L \in (0,1)$.

The SJC has both upper and lower tail dependence parameters. The measures of dependence of the upper and lower tail are respectively its own dependence parameters, τ^U and τ^L. Additionally, τ^U and τ^L independent on each other and hence range freely.

Normal copula: There is no tail dependence in this copula. Instead, its dependence parameter is the linear correlation coefficient.

$$C_N(u_1,u_2|\rho) = \int_{-\infty}^{\phi^{-1}(u_1)}\int_{-\infty}^{\phi^{-1}(u_2)} \frac{1}{2\pi\sqrt{(1-\rho^2)}} \times \exp\left\{\frac{-(r^2-2\rho rs+s^2)}{2(1-\rho^2)}\right\} drds, \quad \rho\in(-1,1).$$

Student-t copula: Similarly, to the Normal copula, the linear correlation coefficient is the measure of dependence for the Student-t copula. However, contrarily to the normal copula, it shows some tail dependence. Actually, it has symmetric tail dependence.

$$C_{ST}(u_1,u_2|\rho,v) = \int_{-\infty}^{t_v^{-1}(u_1)}\int_{-\infty}^{t_v^{-1}(u_2)} \frac{1}{2\pi\sqrt{(1-\rho^2)}} \times \left(1+\frac{r^2-2\rho rs+s^2}{v(1-\rho^2)}\right)^{-\frac{v+2}{2}} drds.$$

Table 1: Characteristics of bivariate copula models

Copula Name	Formula	Parameter	Tail dependence
Normal (N)	$C_N(u,v;\rho)=\Phi\left(\Phi^{-1}(u),\Phi^{-1}(v)\right)$	$\rho\in[-1\ 1]$	Zero tail dependence: $\lambda_L=\lambda_U=0$
Student-t (t)	$C_{ST}(u,v;\rho,\upsilon)=T(t_{\upsilon}^{-1}(u),t_{\upsilon}^{-1}(v))$	$\rho\in[-1\ 1]$	Symmetric tail dependence: $\lambda_U=\lambda_L=2\,t_{\upsilon+1}\left(-\sqrt{\upsilon+1}\sqrt{1-\rho}\,/\sqrt{1+\rho}\right)>0$
Clayton (CL)	$C_{CL}(u,v;\delta)=max\left\{\left(u^{-\delta}+v^{-\delta}-1\right)^{-1/\delta},0\right\}$	$\alpha\in[-1,\infty)\backslash\{0\}$	Asymmetric tail dependence: $\lambda_L=2^{-1/\delta},\lambda_U=0$
Gumbel (GL)	$C_G(u,v;\delta)=\exp\left(-\left(\left(-\log u\right)^{\delta}+\left(-\log v\right)^{\delta}\right)^{1/\delta}\right)$	$\delta\in[1,\infty)$	Asymmetric tail dependence $\lambda_L=0,\lambda_U=2-2^{1/\delta}$
Rotated Gumbel	$C_{RG}(u,v;\delta)=u+v-1+C_G(1-u,1-v;\delta)$		upper tail independence and lower tail dependence
Frank (F)	$C_F(u,v;\delta)=\delta log\left(\left[\left(1-e^{-\delta}\right)-\left(1-e^{-\delta u}\right)\left(1-e^{-\delta v}\right)\right]/\left(1-e^{-\delta}\right)\right)$	$0<\delta<\infty$	Zero tail dependence: $\lambda_L=\lambda_U=0$
Placket	$C_P(u,v;\theta)=\frac{1}{2(\theta-1)}(1+(\theta-1)(u+v))-\sqrt{\left(1+(\theta-1)(u+v)\right)^2-4\theta(\theta-1)uv}$	θ	Zero tail dependence: $\lambda_L=\lambda_U=0$
SJC	$C_{SJC}(u,v;\lambda_U,\lambda_L)=0.5\left(C_{JC}(u,v;\lambda_U,\lambda_L)+C_{JC}(1-u,1-v;\lambda_U,\lambda_L)+u+v-1\right)$	$\lambda_L\in(0,1)$ $\lambda_U\in(0,1)$	$\lambda_U=\lambda_L$
Joe Clayton	$C_{JC}(u,v;\lambda_U,\lambda_L)=1-\left(1-\left\{\left[1-\left(1-u\right)^{\kappa}\right]^{-\gamma}+\left[1-\left(1-v\right)^{\kappa}\right]^{-\gamma}-1\right\}^{-1/\gamma}\right)^{1/\kappa}$	$\lambda_L\in(0,1)$ $\lambda_U\in(0,1)$	$\lambda_t^U=\Delta\left(\omega_U+\beta_U\rho_{t-1}+\alpha_U\frac{1}{q}\sum_{j=1}^{q}\left\|u_{t-j}-v_{t-j}\right\|\right)$ $\lambda_t^L=\Delta\left(\omega_L+\beta_L\rho_{t-1}+\alpha_L\frac{1}{q}\sum_{j=1}^{q}\left\|u_{t-j}-v_{t-j}\right\|\right)$

Notes: λ_L and λ_U denote lower and upper tail dependence, respectively. For Normal copula, $\Phi^{-1}(u)$ and $\Phi^{-1}(v)$ are standard normal quantile functions and Φ is the bivariate standard normal cumulative distribution function with correlation ρ. For Student-t copula, $t_{\upsilon}^{-1}(u)$ and $t_{\upsilon}^{-1}(v)$ are the quantile functions of the univariate Student-t distribution with υ as the degree-of-freedom parameter and T is the bivariate Student-t cumulative distribution function with υ as the degree-of-freedom parameter and ρas the correlation. For SJC copula, $\kappa=1/\log_2(2-\lambda_U)$, $\gamma=-1/\log_2(\lambda_L)$.

2.2 Copula-GARCH model

For $\mathbf{X_t}(x_{1t}, x_{2t})$, $t = 1,2,...,$ a 2-dimensional time series vector, the copula-GARCH model can be specified as

$$H(\mathbf{X_t}|\boldsymbol{\mu}, \mathbf{h_t}) = C_{\theta_{ct}}(F_1(x_{1t}|\mu_1, h_{1t}), F_2(x_{2t}|\mu_2, h_{2t}), \tag{5}$$

where $C_{\theta_{ct}}$ is the copula function with time-varying dependence parameter θ_{ct} and $F_i(x_{it}|\mu_i, h_{it})$, $i = 1, 2$, are the marginal distributions specified as standard univariate GARCH processes.

A GARCH (1,1) model is given by:

$$x_{it} = \mu_i + h_{it}^{1/2}\varepsilon_{it}$$

$$h_{it} = \omega_i + \beta_i h_{it-1} + \alpha_i \varepsilon_{it-1}^2$$

where h_{it} is the conditional variance given past information, ε_{it}, $t = 1, 2,...,$ are i.i.d. random variables, $\omega_i, \beta_{\mathrm{i}}, \alpha_i > 0$ and $\alpha_i + \beta_{\mathrm{i}} < 1$ assuring $h_{it} > 0$ and covariance stationarity, respectively. We also assume that $\varepsilon_{it} \sim \textit{skewed-t}\,(v_i, \lambda_i)$ implying it has a skewed-t distribution. This density is given by

$$g(z|v,\lambda) = \begin{cases} bc\left(1 + \frac{1}{v-2}\left(\frac{bz+a}{1-\lambda}\right)^2\right)^{-(v+1)/2} & z < -a/b \\ bc\left(1 + \frac{1}{v-2}\left(\frac{bz+a}{1-\lambda}\right)^2\right) & \end{cases}$$

$$g(z|v,\lambda) = \begin{cases} bc\left(1 + \frac{1}{v-2}\left(\frac{bz+a}{1-\lambda}\right)^2\right)^{-(v+1)/2} & z < -a/b \\ bc\left(1 + \frac{1}{v-2}\left(\frac{bz+a}{1+\lambda}\right)^2\right)^{-(v+1)/2} & z \geq -a/b, \end{cases}$$

where the constants a, b and c are obtained by

$$a = 4\lambda c\left(\frac{v-2}{v-1}\right), \qquad b = 1 + 3\lambda^2 - a^2, \quad c = \frac{\Gamma\left(\frac{v+1}{2}\right)}{\sqrt{\pi(v-2)}\Gamma\left(\frac{v}{2}\right)}$$

v and λ represent the number of degrees of freedom and asymmetry, respectively. Thus, the conditional distribution function for each marginal is $F_i(x_{it}|\mu_i, h_{it}) = \textit{skewed - } t_{vi,\lambda_i}\left((x_{it} - \mu_i)h_{it}^{-1/2}\right)$.

As stated earlier, the dependence parameter is allowed to vary over time. Its time evolution follows a restricted ARMA(1,10) process, where the intercept term switches according to a first order Markov chain, i.e.,

$$\theta_{ct,S_t} = \Lambda(\omega_c^{S_t} + \beta_c \theta_{ct-1} + \psi_t, \tag{6}$$

where $S_t \sim \text{Markov(P)}$. Here S_t may assume two possible states (or regimes), P is a 2 × 2 transition matrix for these states and the Markov chain is irreducible and ergodic. ψ_t represents a "forcing variable", defined as the mean absolute difference between u_1 and u_2 for R_G and S_{JC}

copulas, given by $\alpha_c \cdot \frac{1}{10}\sum_{j=1}^{10}\left|u_{1,t-j}-u_{2,t-j}\right|$, and the mean of the products between $\alpha_c \cdot \frac{1}{10}\sum_{j=1}^{10}\phi^{-1}(u_{1,t-j})\cdot\phi^{-1}(u_{2,t-j})$ and $\alpha_c \cdot \frac{1}{10}\sum_{j=1}^{10}T_v^{-1}(u_{1,t-j})\cdot T_v^{-1}(u_{2,t-j})$ [3] for the Normal and Student-t copulas across ten previous periods (Patton, 2006). $\Lambda(\cdot)$ is a logistic transformation of each copula function to constrain the dependence parameter in a fixed interval. As a measure of dependence, θ_{ct}, describes features of its associated copula function. So, we use the tail dependence measure calculated as in Definition 1 (except for the Normal copula which has no tail dependence) in this case.

2.3 Estimation

We specify the log-likelihood for the problem as:

$$l(\boldsymbol{\theta}|\mathbf{x_t}) = \sum_{t=1}^{T}\log\left(c_{\theta_{ct}}(F_1(x_{1t}|\theta_1), F_2(x_{2t}|\theta_2)|\theta_{ct,S_t} \times \prod_{i=1}^{2} f_{it}(x_{it}|\theta_i)\right), \tag{7}$$

where $\theta_i = \mu_i, h_{it}$, $i = 1, 2$, and $\boldsymbol{\theta}$ is a vector with all model parameters. Due to the existence of unobserved processes such as h_{1t}, h_{2t} and S_t, it may be computationally expensive to evaluate the likelihood in (7). However, since (7) is a separable function we can use the maximum likelihood estimation procedure in two steps, i.e., we can use the inference function for margins (IFM) method proposed by Joe and Xu (1996).

The IFM method comprises of two steps. In the first step, the parameters of the univariate marginal distributions is estimated. In the second step, these estimates are used to estimate the dependence parameters. Copula-GARCH models became popular because of this procedure. This approach is employed in this study. That is, we model the marginal distributions as univariate GARCH processes and then specify the dependence parameters by the copula function choice.

It is straightforward to fit marginal distributions since it follows the traditional approach for GARCH models. However, the dependence parameter estimation through copulas is not that straight forward because θ_{ct} depends on a non-observable discrete variable S_t which follows a Markov chain. Therefore, this requires additional discussion. We use Kim and Nelson (1999) filter for the estimation.

2.3.1 Copula estimation

Rewriting the log-likelihood in (7) as

$$l(\boldsymbol{\theta}|\mathbf{x_t}) = \sum_{t=1}^{T}\log\left(c_{\theta_{ct}}(F_1(x_{1t}|\mu_1, h_{1t}, \theta_1), F_2(x_{2t}|\mu_2, h_{2t}, \theta_2)|\theta_{ct,S_t} \times \prod_{i=1}^{2} f_{it}(x_{it}|\mu_i, h_{it}, \theta_i)\right)$$

$$= \sum_{t=1}^{T}\log f_{1t}(x_{1t}|\mu_1, h_{1t}; \theta_1) + \sum_{t=1}^{T}\log f_{2t}(x_{2t}|\mu_2, h_{2t}; \theta_2) + \sum_{t=1}^{T}\log c_t(u_{1t}, u_{2t}|\mu_1, \mu_2, h_{1t}, h_{2t}; \theta_{ct}, S_t)$$

$$l(\boldsymbol{\theta}|\mathbf{x_t}) = \ell_{f_1}(\theta_1) + \ell_{f_2}(\theta_2) + \ell_c(\theta_{ct}, S_t),$$

[3] Where ϕ^{-1} and T_v^{-1} are he inverses of the Normal and Student-t c.d.f, respectively.

where $\ell_{f_1}(\theta_1)=\sum_{t=1}^{T}\log f_{1t}(x_{1t}|\mu_1,h_{1t};\theta_1)$, $\ell_{f_2}(\theta_2)=\sum_{t=1}^{T}\log f_{2t}(x_{2t}|\mu_2,h_{2t};\theta_2)$ and $\ell_c(\theta_{ct},S_t)=\sum_{t=1}^{T}\log c_t(u_{1t},u_{2t}|\mu_1,\mu_2,h_{1t},h_{2t};\theta_{ct},S_t)$; $\ell_{f_1}(\theta_1)$ and $\ell_{f_2}(\theta_2)$ are log-likelihood functions used to estimate parameters of the marginal distributions in the first step. Thus, we can move on to the evaluation of $\ell_c(\theta_{ct},S_t)$. Rewriting $\ell_c(\theta_{ct},S_t)$ taking into account non-observable variables and decomposing c_t , we have

$$\ell_c=\sum_{t=1}^{T}\log\left(\sum_{S_t=0}^{1}c_t(u_1,u_2|S_t,w_{t-1})\Pr[S_t|w_{t-1}]\right). \quad (8)$$

We need to calculate the weights $\Pr[S_t|w_{t-1}]$ for $S_t=0$ and $S_t=1$, in order to evaluate the loglikelihood in (8) since the states S_t (only two states in our case) are non-observable. Applying Kim's filter, will result in the following algorithm, which should be iterated through the sample $t=1,...,T$

(a) Prediction of S_t

$$\Pr[S_t=l|w_{t-1}]=\sum_{k=0}^{1}p_{kl}^{t-1}\Pr(S_{t-1}=k|w_{t-1})$$

for $l=0,1$ and $p_{kl}^{t-1}=\Pr(S_t=l|S_{t-1}=k,w_{t-1})$, the transition probabilities between the states k and l.

(b) Filtering of St

$$\Pr(S_t=l|w_t)=\frac{c_t(u_1,u_2|S_t=l,w_{t-1})\Pr[S_t=l|w_{t-1}]}{\sum_{k0}^{1}c_t(u_1,u_2|S_t=k,w_{t-1})\Pr[S_t=k|w_{t-1}]}$$

where $w_t=[w_{t-1},u_{1t},u_{2t}]$. In $t=1$, the filter is initialized using stationary probabilities of S_t for $\Pr(S_0=k|w_0)$.

With this filter, we obtain the probability distribution of S_t given the information set by t. It is however useful to know the distribution of S_t given the full sample information set, since we are dealing with time series. In other words, better estimates can be obtained in the sample by using all T observations (in contrast to a prediction and filtering process). This is because information about the past can be extracted from the future in a time series context.

Therefore, the smoothed probabilities regarding S_t, $\Pr(S_t=l|w_T)=\sum_{k=0}^{1}\Pr(S_t=l,S_t=k|w_T)$, are obtained and $\Pr(S_t=l,S_t=k|w_T)$ can be calculated recursively from the filtered probabilities. This smoothing process works like a backward-smoothing algorithm as follows.

1. Given the filtering process cited above, we obtain $\Pr(S_t=l|w_t)$ for $l=0,1$ and $t=1,...,T$.
2. Then initialize the smoothing algorithm in $t=T$ and go backwards recursively, with $\Pr(S_t=l|w_T)$ being equal to the filtered probability in $t=T$.

3. For each $t = \mathrm{T}-1, \mathrm{T}-2, ..., 1,$ the smoothed probability distribution $\Pr(S_t = l|w_T)$ is given by

$$\Pr(S_t = l|w_T) = \sum_{k=0}^{1} \frac{p_{lk}(t)\Pr(S_t = l|w_t)\Pr(S_{t+1} = k|w_T)}{\sum_{j=0}^{1} p_{jk}(t)\Pr(S_t = j|w_t)}$$

where $p_{lk}(t) = \Pr(S_{t+1} = k|S_t = l, w_t)$ are the transition probabilities between the states l and k.

At $t = 0$ the smoothing algorithm gives us $\Pr(S_0 = l|w_T)$ which can be used as the initial value in the filtering algorithm. Therefore, the forward-filtering–backward-smoothing algorithm is completed and (8) is maximized directly in a numerical fashion in relation to the model.

2.3.2. Computing standard errors by block bootstrap

We use the block bootstrap approach to calculate standard errors of our model for estimating the covariance matrix. We follow Politis and White (2004) and Politis et al. (2007) to calculate the optimal block length. That is, we use the following procedure:
1. Obtain parameter estimates via IFM as described earlier.
2. Sample n/l sub-samples (with replacement) from the observed data and generate a set of time series with size n, where l is the block size.
3. Re-estimate parameters using the generated time series.
4. Repeat steps (2) and (3) R times.
5. Calculate the standard errors for the parameters using the covariance matrix $R^{-1}\sum_{r=1}^{R}(\hat{\Omega}(r)-\hat{\Omega})(\hat{\Omega}(r)-\hat{\Omega})'$, where $\hat{\Omega}(r)$ is the estimated parameter vector for each replication r and $\hat{\Omega}$ is the parameter vector obtained in (1).

2.3.3 Regression analysis using copula parameter, θ

To examine the effect of geopolitical risks on the dynamic dependence relationship between oil and old, we regress, using linear regressions estimated based on ordinary least squares with heteroskedasticity and autocorrelation robust Newey and West (1987) standard errors, θ from the best copulas on three versions of GPR, namely the overall GPR (GPR), GPR due to threats (GPRT) and actual acts (GPRA).

3. Data

We used daily data on gold prices and West Texas Intermediate Institute (WTI) crude oil spot prices covering from 2 January 1985 to 30 November 2017. We use gold fixing price at 3:00 P.M. (London time) in London Bullion Market, based in U.S. Dollars, and WTI oil prices measured in US dollar per barrel. Both data were sourced from the FRED database of the Federal Reserve Bank of St. Louis.

Since we anticipate that geopolitical risks may influence the safe haven ability of gold for oil price, we also obtained daily data on GPR covering from the same time period. The GPR data were sourced from Caldara and Iacoviello (2018), which is available for download at: https://www2.bc.edu/matteo-iacoviello/gpr.htm. Caldara and Iacoviello (2018) construct the GPR index by counting the occurrence of words related to geopolitical tensions, derived from automated text-searches in 11 leading national and international newspapers (The Boston Globe, Chicago Tribune, The Daily Telegraph, Financial Times, The Globe and Mail, The Guardian, Los

Angeles Times, The New York Times, The Times, The Wall Street Journal, and The Washington Post). They then calculate an index by counting, in each of the above-mentioned 11 newspapers, the number of articles that contain the search terms above for every day starting in 1985. The index is then normalized to average a value of 100 in the 2000-2009 decade. The search identifies articles containing references to six groups of words: Group 1 includes words associated with explicit mentions of geopolitical risk, as well as mentions of military-related tensions involving large regions of the world and a U.S. involvement. Group 2 includes words directly related to nuclear tensions. Groups 3 and 4 include mentions related to war threats and terrorist threats, respectively. Finally, Groups 5 and 6 aim at capturing press coverage of actual adverse geopolitical events (as opposed to just risks) which can be reasonably expected to lead to increases in geopolitical uncertainty, such as terrorist acts or the beginning of a war. Based on the search groups above, Caldara and Iacoviello (2018) further disentangle the direct effect of adverse geopolitical events from the effect of pure geopolitical risks by constructing two indexes. The Geopolitical Threats (GPRT) index only includes words belonging to Search groups 1 to 4 above. The Geopolitical Acts (GPRA) index only includes words belonging to Search groups 5 and 6. The GPR indexes are found to be stationary in their raw level-form. Note our sample size is contingent upon data availability of the geopolitical risks indices at the time of writing this paper.

The first panel of Figure 1 presents the time series plots of the raw gold and oil prices. We observe a sharp decline in the price of oil around the 2008-2009 global crisis. Although gold prices also declined around this period, the fall is not as sharp as that of oil prices. Towards the later end of the sample, we can also witness another decline. From 2007 there seems to be a sort of unexpected highs and lows in the trend for the two series. Overall, there seem to be visual evidence of consistent positive relationship between the two series. However, this will be confirmed using Copula models. The gold and oil return series (first logged difference) are presented in the second and third panels of Figure 1, respectively. Both return series exhibit volatility clustering with both low and high frequency volatility suggesting that some form of GARCH-type modeling may be appropriate. The statistical properties of the gold and oil returns are shown in Table 2. Both gold and oil have positive returns. Gold has larger average returns than that of oil while oil's returns seem to be relatively more volatile as indicated by the standard deviation. Both are negatively skewed (negative asymmetry) which is an indication of greater probability of larger decreases in their returns. The kurtosis values are greater than 3 for both series, an indication of fat tails. The non-normality of gold and oil return series is further confirmed by the Jarque-Bera results. The results suggest the existence of ARCH effects. The two unit-root tests (ADF and PP) and a stationarity test (KPSS) indicate that the return series are stationary. There is a positive but weak correlation between oil and gold returns suggesting lack of potential diversification benefits.[4]

[4] As an additional check in this regard, across frequency domain, we used the co-spectral analysis of Kim and In (2003). As can be seen from Figure A1 in the Appendix A, the two returns are always in-phase across various frequencies, with dependence increasing at longer frequencies, suggesting lack of diversification benefits in the long-run. Further, in Figure A2 in the Appendix A of the paper, we present quantiles-based coherency (as developed by Baruník and Kley (2019)) between gold and oil returns across various quantiles. The figures in the left panel correspond to Real (Re) and the right panel for imaginary (Im) parts of the quantile coherency estimates for weeks (W), months (M) and years (Y), along with the 95 percent confidence intervals. Note, quantiles provide an indirect way of studying the time-varying nature of the relationship between the two variables, as they correspond to different states of the gold and oil markets. As can be seen, in general, the relationship between these two variables tend to be positive, but there is also some evidence of negative coherency, especially at longer frequencies. This result tends to suggest that it

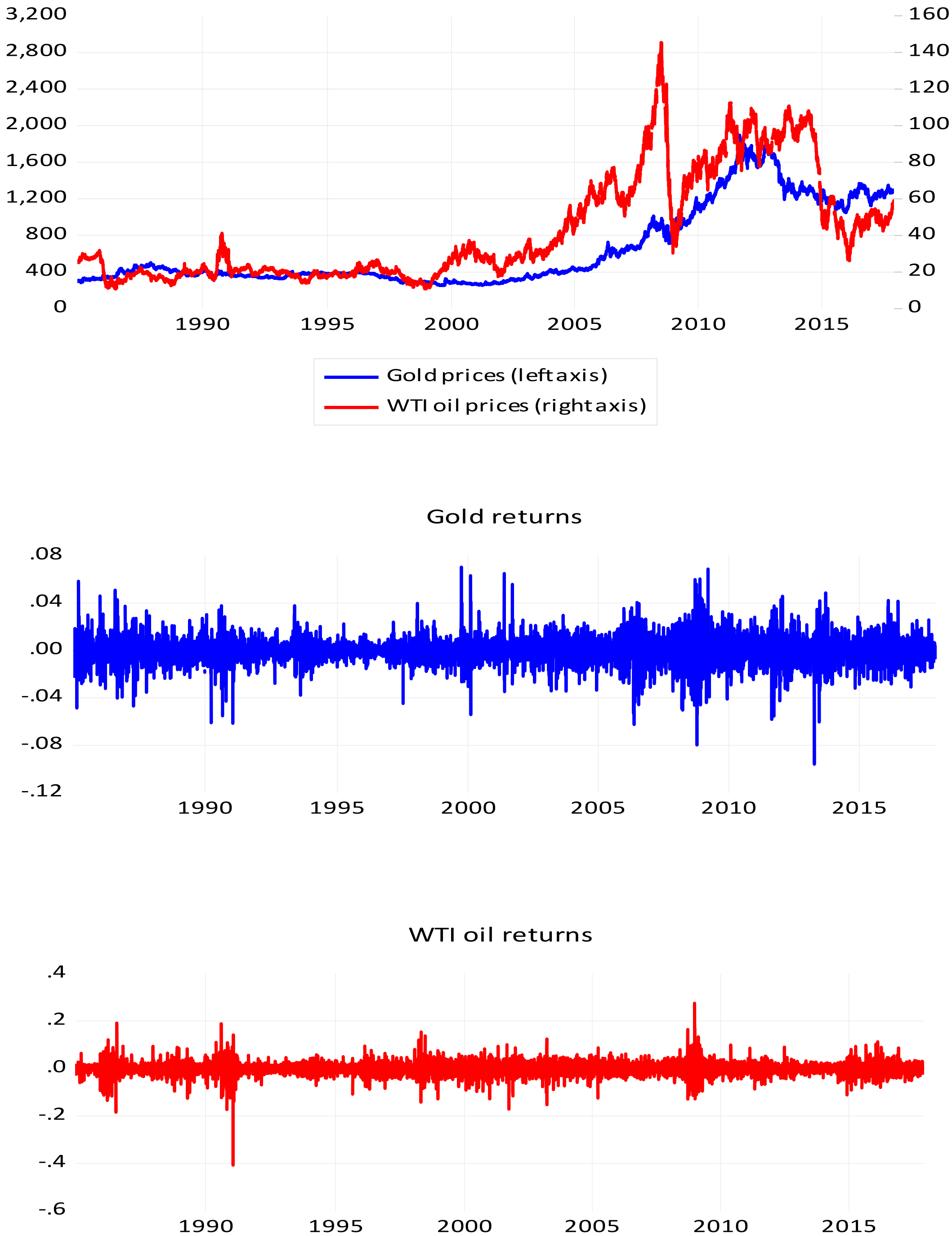

Figure 1. Gold and West Texas Intermediate Crude Oil Prices and Returns

Table 2. Statistical properties

is perhaps important to study the conditional dependence conditional on the regimes of these two markets, which is what we aim to do via the regime-switching time-varying copula models.

	Oil	Gold
Mean	9.78E-05	0.000177
Median	0.000478	0.000177
Maximum	0.275638	0.07006
Minimum	-0.4064	-0.095962
Std. Dev.	0.025325	0.010177
Skewness	-0.48125	-0.180598
Kurtosis	18.03199	9.253237
Jarque-Bera	76574.38***	13241.28***
ADF	-26.494***	-19.488***
PP	-91.61***	-43.511***
KPSS	0.0575	0.1927
Q(10)	51.440***	21.653**
$Q^2(10)$	756.84***	1049.6***
ARCH	72.8523***	01592199***
Correlation		
Oil	1	
Gold	0.12466	1

Notes: ADF, PP and KPSS are the empirical statistics of the Augmented Dickey-Fuller (1979), and the Phillips-Perron (1988) unit root tests, and the Kwiatkowski et al. (1992) stationarity test, respectively. ARCH-LM(1) test of Engle (1982) is to check the presence of ARCH effects. ***, **, * denote the rejection of the null hypotheses of normality, no autocorrelation, unit root, stationarity, and conditional homoscedasticity at the 1%, 5% and 10% significance levels, respectively.

To model the dependence structure between gold and oil, the analysis was performed using the two log-returns. However, to have a richer picture of the degree and structure of dependence in the gold and oil markets across various investment horizons, the wavelet decomposition method was also considered following Tiwari et al. (2013) and Mensi et al. (2016). To do this, we decompose the time series into different scales using the multi-resolution analysis (MRA) design method. The MRA interpretation of order up to *S9* is presented in Table 3. Scales *D1-D3* denote a daily scale which can be interpreted as low scales, implying they could be relevant for low scale speculative traders. Scales higher than *D3* and perhaps until *D6* can be interpreted as intermediate scales while scales higher than *D6* represent high scale data. These wavelet time scales could also be considered as short-term, medium-term and long-term investment horizons respectively.

Table 3. Scale interpretation of the MRA scale levels.

Scale	daily scale
D1	2 ~ 4 days
D2	4 ~ 8 days
D3	8 ~ 16 days
D4	16 ~ 32 days
D5	32 ~ 64 days
D6	64 ~ 128 days
D7	128 ~ 256 days
D8	256 ~ 512 days
D9	512 ~ 1024 days
S9	More than 1024 days

Note: MRA is the multi-resolution analysis. *D1-D3* represent a daily scale which can then be interpreted as low scales, whereas scales higher than *D3* (maybe until *D6*) can be interpreted as intermediate scales. Scales Higher than *D6* represent high scale data.

4. Results

4.1 Marginal distribution results

The aim of the study is to examine the hedge and safe haven effectiveness of gold for oil returns. As a first step in the analysis, various forms of ARMA-SPLINE-GARCH marginal distribution models were fitted considering different combinations of $\boldsymbol{p}$, $\boldsymbol{q}$, $\boldsymbol{r}$ and $\boldsymbol{m}$ for the values ranging from zero lag to a maximum of 2 lags. The best model is selected using the Akaike Information Criterion (AIC). The parameter estimates of the best marginal model, ARMA(1,0)-SPLINE-GARCH(1,1) model with 5 knots (splines) are presented for each return series in Table 4. The estimates of conditional mean (AR 1) are negative and statistically significant for both gold and oil returns albeit. The small size of the coefficients depicts some form of very weak dependence on the past returns.

From the conditional variance equation, we observe that the ARCH effects (alpha 1) is statistically significant and positive as expected. Similarly, the coefficient of the GARCH component (beta 1) is positive and statistically significant. The magnitude of the GARCH parameter (less than but close to 1) for each return series, indicates high volatility persistence. The sum of the ARCH and GARCH coefficients are less than one (0.9852), showing the stability of our ARMA(1,0)-SPLINE-GARCH(1,1) model specification. The knot coefficients (Spline_Vi) are also statistically significant for the four interior knots for the oil return series and for all five interior knots for the gold return series suggesting changes in the curvature of the time trend of these series during some periods. These results are consistent with the pattern of volatility witnessed in Figure 1.

There is evidence of significant asymmetry or leverage effects as well as fat tails in the error terms. This indicates a heavy tail to the left for the marginal distributions meaning that large negative returns in downturn periods are more likely than large positive returns. In other words, the negative residuals of oil and gold (bad news) tend to increase the variance (conditional volatility) more than positive shocks (good news) of the same magnitude. This leverage effects could be due to information asymmetry, arbitrage activities, heterogeneity, and/or contract liquidity within particular markets (Raza et al., 2018). These results also indicate the existence of potential dependence in the tails of the joint distribution of oil and gold returns.

The appropriateness of the selected model could further be judged using the diagnostic statistics. The Ljung–Box Q statistics indicate that there is neither autocorrelation nor squared autocorrelation in the residual terms. More so, the McLeod and Li (1983) test results do not reject the null of no squared residual autocorrelations or no conditional heteroscedasticity. Therefore, one can conclude there are no remaining ARCH effects.

Table 4. Estimates of the marginal distribution models (ARMA(1,0)-SPLINE-GARCH(1,1) model)

	Oil			Gold		
Mean equation						
	Coefficient	Std.Error	p-value	Coefficient	Std.Error	p-value
Cst(M)	0.000239	0.0002	0.2311	-2.7E-05	7.78E-05	0.7307
AR(1)	-0.02598**	0.011143	0.0197	-0.0417***	0.010258	0.00000
Variance equation						
Cst(V) x 10^4	3.0938***	0.69119	0.0000	1.7553***	0.35213	0.0000
Spline_1 (V)	4.9511***	1.8181	0.0065	-27.80***	2.4925	0.0000
Spline_2 (V)	2.5667	2.935	0.3819	75.889***	6.2299	0.0000
Spline_3 (V)	-22.84***	2.2419	0.0000	-52.65***	7.4745	0.0000
Spline_4 (V)	1.8008	4.1583	0.665	-20.346***	6.7678	0.0027
Spline_5 (V)	52.186***	4.2159	0.0000	19.57*	10.138	0.0535
ARCH(α_1)	0.0706***	0.007787	0.0000	0.0583***	0.005975	0.0000
GARCH(β_1)	0.9146***	0.008875	0.0000	0.924***	0.007572	0.0000
Asymmetry	-0.064***	0.015306	0.0000	-0.033**	0.013921	0.0183
Tail	5.733***	0.36374	0.0000	4.2862***	0.21518	0.0000
Diagnostic tests						
Log-Likelihood	19873.585			27136.512		
AIC	-4.8937			-6.6974		
$Q(10)$	6.985			17.007		
	[0.6386]			[0.0486]		
$Q^2(10)$	6.486			11.661		
	[0.593]			[0.1669]		
McLeod-Li(10)	1.0633			1.0223		
	[0.387]			[0.421]		

Notes: The lags p, q, r and m are selected using the AIC for different combinations of values ranging from 0 to 2. $Q(10)$ and $Q(10)(2)$ are the Ljung-Box statistics for serial correlation in the model residuals and squared residuals, respectively, computed with 10 lags.. The p-values (in square brackets) below 0.05 indicate the rejection of the null hypothesis. ***, **, * denote, respectively, significance at the 1%, 5%, and 10% levels.

4.2. Dependence structure (Copula) results

The estimated results of the dependence structure between gold and oil using the time-invariant, traditional time-varying and time varying Markov copulas are presented in Table 5. The results are presented for the returns and wavelet decomposed series, where wavelet decomposition is applied to the standardised residuals extracted from the marginal models. We use the log likelihood to select the best copula model. Lower likelihood values indicate better model. Our results provide strong evidence that the time-varying Rotated Gumbel Markov copula is the best specification for the return series while the time-varying normal Markov copulas provide the best fit for all the wavelet series. Therefore, the subsequent discussions will focus on the results from these best models.

We observe a substantial change in the intercept term, ω, in the equation that describes the dependence dynamics between the low and high regimes especially for the wavelet series. The low and high regimes seem to be moderately persistent as indicated by the values of the probabilities p and q. These results indicate that the dependence structure between gold and oil is Markov-switching time-varying. Therefore, constant and conventional time-varying copula models may not be adequate to capture this relationship. The estimates of β for both the raw returns and wavelet series are significant, implying that the dependence between gold and oil is time-varying. The nature of the dependence can be inferred from the sign of the β estimate. The results as summarized in Table 6 indicate a positive dependence structure for the return series. This implies that gold returns is not a good hedge for oil and hence does not protect investors against losses from rising oil prices since both co-move in the same direction. This is consistent with Reboredo (2013) and Balcilar et al. (2018).

Table 5. Estimates for the bivariate copula models

	Returns	D1	D2	D3	D4	D5	D6	D7	D8	D9	S9
Panel A: Parameter estimates for time-invariant copulas.											
Normal copula											
ρ	0.114	0.060	0.156	0.207	0.189	0.157	0.219	0.119	0.160	0.359	0.281
Log-lik.	-52.849	-14.63	-100.2233	-0.1769	-0.1472	-0.1007	-0.1982	-0.0583	-0.1054	-0.5614	-0.3336
Clayton copula											
α	0.132	0.071	0.165	0.2245	0.2048	0.172	0.2099	0.1331	0.1745	0.461	0.326
Log-lik.	-58.589	-19.101	-84.0575	-0.1467	-0.1242	-0.0868	-0.1235	-0.0584	-0.104	-0.5025	-0.2897
Rotated Clayton											
α	0.1084	0.0658	0.1667	0.219	0.197	0.1716	0.2449	0.1159	0.1295	0.4264	0.2436
Log-lik.	-39.001	-16.1391	-86.234	-0.139	-0.1154	-0.0837	-0.1692	-0.045	-0.0581	-0.4396	-0.1472
Plackett copula											
δ	1.4057	1.1939	1.579	1.816	1.7369	1.7016	1.8269	1.3824	1.3995	2.4002	2.0801
Log-lik.	-49.072	-13.1273	-88.681	-0.1536	-0.1314	-0.1166	-0.164	-0.0473	-0.051	-0.3503	-0.2684
Frank copula											
δ	0.6581	0.339	0.8865	1.1729	1.0838	1.0152	1.2185	0.6507	0.6750	1.7894	1.583
Log-lik.	-47.126	-12.5471	-85.0439	-0.1481	-0.1271	-0.1099	-0.1625	-0.0474	-0.0508	-0.3435	-0.2766
Gumbel copula											
δ	1.1	1.1	1.1	1.129	1.1145	1.1071	1.1387	1.1	1.1	1.2518	1.1547

Log-lik.	-46.104	15.1113	-99.5964	-0.163	-0.1341	-0.1056	-0.1845	-0.0535	-0.0314	-0.5195	-0.1664
Rotated Gumbel copula											
δ	1.1	1.1	1.1	1.1303	1.1183	1.1046	1.127	1.1	1.1	1.262	1.1788
Log-lik.	-59.216	8.0071	-98.9218	-0.1629	-0.1338	-0.1104	-0.1393	-0.0671	-0.1027	-0.6055	-0.2587
Student-t copula											
ρ	0.11267	0.0573	0.1539	0.2026	0.1863	0.1665	0.2184	0.1172	0.1573	0.3287	0.2804
υ	11.1639	10.701	11.839	13.455	13.605	8.9937	99.990	14.239	99.993	7.9708	99.999
Log-lik.	-82.289	-47.4133	-126.9136	-0.197	-0.1691	-0.1443	-0.1981	-0.0781	-0.1028	-0.5972	-0.3247
SJC copula											
λ_U	0.0049	0.00023	3.07E-02	5.37E-02	4.04E-02	3.30E-02	8.85E-02	9.10E-03	1.42E-03	1.69E-01	1.06E-02
λ_L	0.0220	0.0018	0.028813	0.05864	0.048974	0.033224	0.028741	0.023875	0.054171	0.200488	0.156666
Log-lik.	-71.607	-26.21	-119.2823	-0.1951	-0.163	-0.1187	-0.1961	-0.0783	-0.113	-0.6954	-0.2686
Panel B: Parameter estimates for time-varying copulas.											
TVP-Normal											
ψ_0	0.0205	0.1657	0.249	0.473	0.331	0.346	0.0654	0.0259	-0.0339	0.0083	-0.031
ψ_2	0.033	0.538	0.256	0.701	0.756	0.677	0.4655	0.2338	0.2176	0.2676	0.1563
ψ_1	1.782	-1.950	-0.104	-2.024	-1.105	-2.042	0.531	1.7137	1.827	2.1007	2.079
Log-lik.	-64.665	-79.5621	-152.5796	-0.4174	-0.6455	-0.5458	-1.0115	-1.3298	-1.4989	-2.6984	-1.9499
TVP Rotated Gumbel copula											
ω_U	-0.54389	2.09419	0.83131	1.57126	0.9317	0.3911	0.5683	0.6324	0.7137	0.9671	0.6258
α_U	0.88161	-1.31685	0.02691	-0.40551	0.094071	0.35579	0.27314	0.27573	0.25830	0.20830	0.28237
β_U	-0.41113	-1.30833	-1.7048	-2.11239	-1.9085	-1.30059	-1.35629	-1.3860	-1.55194	-2.00759	-1.16938
Log-lik.	-77.048	-77.048	-77.048	-77.048	-77.048	-77.048	-77.048	-77.048	-77.048	-77.048	-77.048
TVP-SJC											
ω_U	0.38853	3.43496	2.1707	4.87513	5.54071	4.98403	1.78003	3.1307	-7.0605	0.67847	-0.4639
α_U	-17.2823	-24.9999	-18.6329	-24.8694	-24.9996	-24.9999	-24.999	-15.5735	-2.8969	-10.923	-13.809
β_U	0.9773	-7.58821	-0.68675	-4.1352	-4.26013	-4.03413	0.674679	-3.4830	-0.0008	0.7969	3.685949
ω_L	-0.1693	3.360509	1.89039	3.8508	4.751629	5.008997	-2.196315	4.784823	2.4505	1.8055	5.502299
α_L	-12.2236	-24.9999	-17.1091	-21.0695	-23.9389	-24.9999	-12.3013	-21.514	-24.999	-10.571	-24.9856
β_L	3.22851	-2.7954	-1.144952	-4.2489	0.453	-4.48690	0.079612	-3.35693	-0.247	0.1045	-4.48359
Log-lik	-84.381	-71.7824	-233.3782	-0.525	-0.8505	-0.9765	-0.8389	-1.555	-1.2992	-2.7964	-2.1935
TVP Student-t											
ψ_0	0.00789	0.15807	0.22620	0.48859	0.03873	0.22141	0.04998	0.01757	-0.00535	-0.00437	-0.02064
ψ_2	0.010316	0.18319	0.104027	0.29751	0.09967	0.23661	0.1927	0.1269	0.11463	0.1156	0.10068
ψ_1	1.91151	-1.88824	0.05395	-2.02466	1.6061	0.03026	1.20764	1.82588	1.90231	2.0593	2.0655
υ	4.99999	4.99999	4.99999	4.99999	4.99999	4.99999	4.99999	4.99999	4.99999	4.9999	4.99999
Log-lik.	-55.449	-44.1503	-119.139	-0.2961	-0.3897	-0.4453	-0.7242	-0.9834	-1.0962	-2.2236	-1.5334
TVP Clayton											
ψ_0	0.474237	1.038838	1.1136	1.506	1.30831	1.06662	1.02385	1.09679	1.1459	1.4116	1.248
ψ_2	0.60582	-1.00299	-0.0138	-0.416	0.02137	-1.8882	0.21331	0.2231	0.2158	0.1671	0.207

ψ_1	-0.58792	-1.7429	-2.1733	-2.614	-2.3679	-1.1737	-1.6157	-1.6436	-1.7921	-2.3437	-2.118
Log-lik.	-69.472	-58.4388	-185.7037	-0.387	-0.6266	-0.3188	-0.9654	-1.3306	-1.5125	-2.6701	-1.6756
TVP Rotated Clayton											
ψ_0	0.80253	0.60385	1.10922	1.48952	0.53951	1.04957	1.19641	1.16038	1.01106	1.2082	1.18495
ψ_2	-0.32915	0.50947	0.01292	-0.29143	-0.9312	-1.88246	-1.25014	0.1866	-1.71675	0.20839	0.21746
ψ_1	-1.30042	-1.14694	-2.18679	-2.71946	-1.00675	-1.26571	-0.9379	-1.68551	-1.14058	-2.01703	-2.00449
Log-lik.	-48.228	-41.7308	-191.6357	-0.4131	-0.1529	-0.3146	-0.3107	-1.2402	-0.3799	-2.2332	-1.7505
TVP Gumbel											
Ω	0.0121	2.08785	0.81788	1.50287	0.90269	0.38371	0.68649	0.66955	0.35501	0.69389	0.75742
β	0.43988	-1.31011	0.03978	-0.34177	0.11798	0.35999	0.21705	0.25919	0.3562	0.26307	0.25469
α	-0.68135	-1.28181	-1.70856	-2.15118	-1.92596	-1.30117	-1.4624	-1.40386	-0.8174	-1.5844	-1.7211
Log-lik.	-66.797	-63.5583	-219.591	-0.4688	-0.7478	-0.7993	-1.2183	-1.5628	-1.4209	-2.8721	-2.078
Panel C: Parameter estimates for time-varying Markov copula											
Time-varying Normal Markov copula											
$\omega_{c,N}^0$	0.0180	-0.22146	-0.11118	-0.4117	-0.27587	-0.62325	-0.27657	-0.20417	-0.10504	-0.0440	-4.2426
$\omega_{c,N}^1$	0.29110	3.8718	1.3587	3.40588	2.90707	3.33892	2.8353	2.2301	2.2536	2.06023	0.51006
β_c, N	1.7554	-2.00513	0.40552	-1.99523	-0.38227	-0.74270	0.27593	1.06747	1.67759	2.01120	-1.57889
$\alpha_{c,N}$	0.03015	0.49454	0.05875	0.75654	0.73490	0.50459	0.49408	0.40896	0.22658	0.2319	2.0911
p	0.38355	0.13546	0.38176	0.38788	0.37972	0.44177	0.41569	0.42918	0.42123	0.4322	0.51333
q	0.61645	0.86454	0.61823	0.61211	0.62027	0.55823	0.5843	0.57082	0.57877	0.56779	0.48666
Log-lik.	-84.549	-194.822	-331.062	-0.7996	-1.366	-1.9283	-2.3136	-2.8026	-3.1304	-4.2028	-3.7348
Time-varying Clayton Markov copulas											
$\omega_{c,C}^0$	0.3940	-0.63819	0.76445	0.96260	0.65986	0.68605	0.70452	0.34656	0.7204	0.74329	0.72544
$\omega_{c,C}^1$	-1.32319	-2.7164	-1.47987	-1.64775	-0.95079	-0.95708	-0.95973	-1.20541	-0.96192	-0.9707	-0.96399
$\beta_{c,C}$	0.5356	0.30639	0.16159	-0.04250	-0.24374	-0.23886	-0.23803	-0.20754	-0.23319	-0.22936	-0.23654
$\alpha_{c,C}$	-0.36088	1.24173	-1.42736	-1.68524	-0.12858	-0.12357	-0.13107	0.00849	-0.13416	-0.14821	-0.11699
p	0.36407	0.15019	0.26742	0.19542	0.42856	0.42863	0.42863	0.42899	0.42863	0.42866	0.42865
q	0.63593	0.8498	0.73257	0.80457	0.57143	0.57137	0.57137	0.57100	0.57136	0.57134	0.57135
Log-lik	-74.861	-86.944	-210.9819	-0.4845	-0.5374	-0.8376	-0.9951	-1.7696	-1.2825	-2.1299	-1.6877
Time-varying Rotated Gumbel Markov copulas											
$\omega_{c,RG}^0$	-0.45813	0.42463	0.74707	2.48379	1.5673	1.45268	1.51039	1.46272	0.5701	1.63561	0.81961
$\omega_{c,RG}^1$	-0.59799	-0.22286	0.17497	1.05837	0.64438	0.33947	0.57168	0.82352	-0.0339	1.02237	0.46136
$\beta_{c,RG}$	0.80733	0.34371	0.20059	-0.30612	0.08823	0.08881	0.12972	0.15797	0.29075	0.14148	0.24167
$\alpha_{c,RG}$	-0.21811	-0.27828	-0.81446	-1.41653	-1.36053	-0.71282	-1.10817	-1.92644	-0.01062	-2.17761	-1.37652
p	0.54312	0.84951	0.66296	0.72076	0.67996	0.60275	0.63075	0.57005	0.42887	0.60077	0.45481
q	0.4569	0.15049	0.33704	0.27924	0.32004	0.39725	0.36925	0.42995	0.57113	0.39923	0.54519
Log-lik	-90.127	-130.959	-274.2829	-0.592	-1.0417	-1.5259	-1.8699	-2.3449	-1.8738	-3.7979	-2.5526

Time-varying Rotated Clayton Markov copulas											
$\omega^{0}_{c,RC}$	-0.5219	-0.5908	0.77397	0.98407	0.68283	0.57599	0.71269	0.71093	0.71469	0.04339	0.71917
$\omega^{1}_{c,RC}$	-1.18871	-3.10989	-1.75205	-1.78247	-0.95314	-0.98501	-0.96026	-0.95821	-0.9599	-0.92309	-0.96224
$\beta_{c,RC}$	1.4059	0.26088	0.18613	-0.02146	-0.24507	-0.25383	-0.23906	-0.23137	-0.23512	-0.23753	-0.23495
$\alpha_{c,RC}$	0.2824	1.04305	-1.46014	-1.8031	-0.11636	0.00055	-0.12444	-0.1434	-0.12635	-0.16050	-0.12807
p	0.34393	0.0875	0.22669	0.21351	0.42857	0.42854	0.42863	0.42863	0.42863	0.62806	0.42866
q	0.65607	0.91245	0.77330	0.78649	0.57143	0.57146	0.57137	0.57137	0.57137	0.37194	0.57134
Log-lik.	-48.742	-89.1366	-225.7338	-0.5481	-0.525	-0.9716	-1.1275	-1.0012	-1.1077	-2.0476	-1.3405
Time-varying Gumbel Markov copulas											
$\omega^{0}_{c,G}$	1,41543202	1.68459994	0.96039629	2.62150028	1.48629434	1.39873162	1.40343305	0.57430077	**0.56918605**	1.32108787	0.62158053
$\omega^{1}_{c,G}$	1.03915	1.37477	0.33312	1.08625	0.60044	0.32277	0.49854	-0.03921	**-0.03139**	0.82797	-0.0216
$\beta_{c,G}$	-0.62472	-0.67536	0.16119	-0.28734	0.0957	0.10106	0.11698	0.28996	**0.29095**	0.16877	0.27772
$\alpha_{c,G}$	-0.88607	-1.47510	-1.03554	-1.51446	-1.29717	-0.70503	-0.98136	-0.03036	**-0.00882**	-1.87394	0.00126
p	0.52207	0.55461	0.72712	0.73565	0.66226	0.60036	0.59113	0.42896	0.42894	0.53913	0.42884
q	0.47793	0.44539	0.27288	0.26436	0.33774	0.39964	0.40887	0.57104	0.57107	0.46087	0.57116
Log-lik.	-86.554	-75.8517	-281.3256	-0.6261	-1.0485	-1.5148	-1.8626	-1.7318	-1.8462	-3.6546	-1.8652
Time-varying SJC Markov copulas											
$\omega^{0}_{c,U}$	0.39186	3.43478	2.17085	5.39895	**6.00902**	**5.25136**	**-0.3788**	1.81118	1.30632	**1.36429**	-3.37585
$\omega^{1}_{c,U}$	-0.16939	3.35948	1.89029	4.75935	**4.86729**	**5.97559**	**5.19819**	0.08387	1.65165	**1.19236**	2.9128
$\beta_{c,U}$	-22.643	-18.0513	**-19.787**	-22.4834	**-0.11396**	**-13.876**	**-3.3968**	-3.33759	-1.73658	**-0.97139**	-3.39259
$\alpha_{c,U}$	*-22.427*	-13.3687	**-19.803**	-22.6742	**0.82529**	**1.71997**	**0.97065**	-3.37451	-1.60179	**-1.86035**	-3.2770
$\omega^{0}_{c,L}$	0.95552	-7.58877	-0.68683	-3.58883	**-4.12405**	**-4.72812**	**1.33478**	0.61019	0.39021	**0.87017**	0.42019
$\omega^{1}_{c,L}$	3.2281	-2.79391	-1.14491	-3.88320	**-2.58041**	**-3.50590**	**-2.8666**	-1.55847	0.66509	**0.46244**	-0.04512
$\beta_{c,L}$	-17.3016	-24.9994	-18.6341	-17.5363	**-12.5832**	**-1.59628**	**-8.38409**	-2.79185	-1.70386	**-3.21836**	-6.76690
$\alpha_{c,L}$	-12.222	-24.9997	-17.1084	-14.2343	**-11.621**	**-17.9895**	**-11.3241**	-2.71104	-1.84403	**-2.99848**	-8.3576
p	0.59606	0.59918	0.59996	0.54079	0.60244	0.5752	0.38451	0.4933	0.47991	0.5061	0.5120
q	0.40394	0.40082	0.40004	0.45921	0.39756	0.42478	0.61548	0.50668	0.52009	0.49383	0.4879
Log-lik.	-84.369	-71.7647	-233.3774	-0.5934	-1.0047	-1.4253	-1.6502	-1.8336	-1.8142	-3.0279	-2.4484
Time-varying T Markov copulas											
Convergence was not achieved in any of the models, hence results are not presented											

Notes: This table reports the ML estimates for the different static and dynamic bivariate copula models for the gold-oil return and each of the time scale indicated in each column. All coefficients are significant except the bold once that are insignificant, italic coefficient are significant at 5% level of significance. The minimum loglikelihood value (value on bold) indicates the best copula fit.

However, across different time scales (investment horizons), which takes the heterogeneity of market agents into account, the dependence structure vary. In the short- and medium-term investment horizons, we find mostly a negative dependence between gold and oil except for D2. Contrary to this, the dependence structure in the long-term is mostly positive except for S9. This implies that gold is a good hedge against oil price in the short- and medium-term, thus highlighting the diversification importance of gold for short- and medium-term (traders and speculators) investors. In this instance, gold is a refuge or protector for market participants who are interested in the short- and medium fluctuations. However, gold cannot compensate long- term investors (institutional investors and central banks) for losses arising from oil price increases since both commodities co-move in the same direction in the long-term. Gold is therefore not a good hedge in the long-term. This further implies that long-term investors may not reap any benefit from portfolio diversification regarding risk management. Diversification benefits generated by portfolios composed of gold and oil commodity may potentially decrease as gold co-crash with oil.

Table 6. Summary of empirical results

	Oil-Gold	
Scale	**Best copula**	**Dependence structure**
Returns	Time-varying Rotated Gumbel Markov copulas	+
D1	Time-varying Normal Markov copula	-
D2	Time-varying Normal Markov copula	+
D3	Time-varying Normal Markov copula	-
D4	Time-varying Normal Markov copula	-
D5	Time-varying Normal Markov copula	-
D6	Time-varying Normal Markov copula	+
D7	Time-varying Normal Markov copula	+
D8	Time-varying Normal Markov copula	+
D9	Time-varying Normal Markov copula	+
S9	Time-varying Normal Markov copula	-

Note: This table reports the best copula function for oil-gold pairs for raw returns and at each time scale ranging from D1 to D9 and S9 as well as their dependence structure.

Next, we turn to tail dependence. The time evolution of the dependence parameter for the low and high regimes are shown in Figure 1. Since the returns series is best fitted by the rotated Gumbel copula, they exhibit asymmetric time-varying tail dependence. There is greater dependence in the negative tail, with the degree of dependence in the positive tail being equal to zero (Shahzad et al., 2018). Specifically, this implies that the return series have negative tail asymmetric dependence. The wavelet series which are captured best by the normal copula exhibit zero upper and lower (symmetric) tail dependence and this is evidence in favour of the safe haven ability of gold for oil price movement (Reboredo, 2013) albeit in a time-varying fashion. From Figure 1, we observe that the tail dependence structure varies over time for both low and high dependence regimes. For the raw return series, this is clearly positive in both regimes with higher values in the lower regime than the upper regime. For the wavelet series, the dependence parameter is mostly positive for the high regime but fluctuates between positive and negative in the low regime. The dependence parameters in general seem to be high around 2008/2009 global financial crisis period. Recalling that a safe haven is confirmed if an asset is uncorrelated or negatively correlated with another asset in times of market crisis, one may conclude that gold is a safe haven for oil.

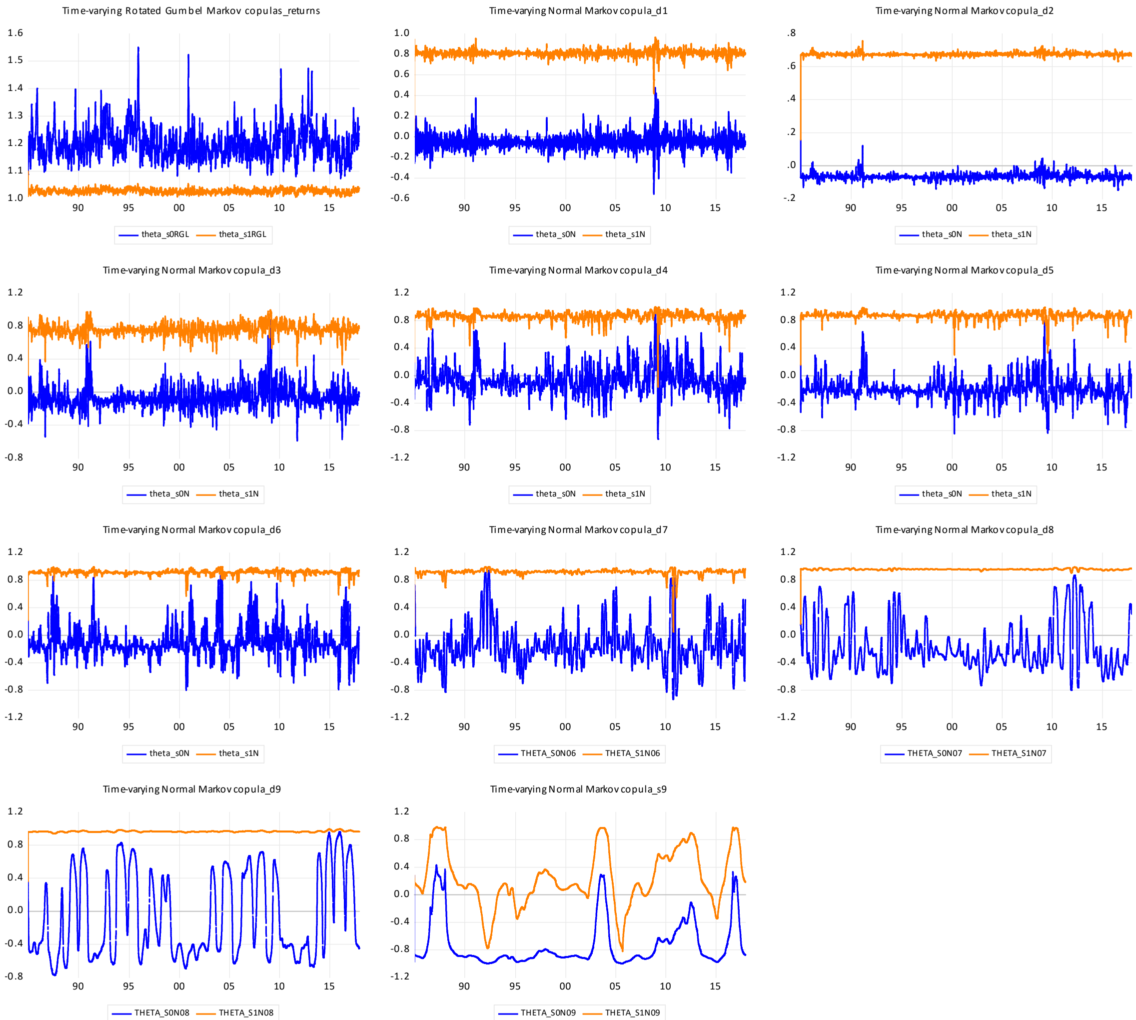

Figure 2. Dependence parameter plots

4.3 The effects of geopolitical risks on the dynamic dependence relationship

To examine the effects of geopolitical risks (GPR) on the correlation between gold and oil prices, we estimated a regression model using dependence parameter estimates from the best copula models for both the return and wavelet series. We estimated the models for the overall GPR (GPR), GPR due to threats (GPRT) and actual acts (GPRA). Table 7 presents the regression based on the rotated Gumbel and Normal time-varying Markov copula models. Our findings show that there is a statistically significant effect of GPR, GPRT and GPRA on the gold and oil dependence dynamics. The results vary depending on the regime and whether we consider the returns or the wavelet series. Overall, geopolitical risks tend to have negative effect on the return series and in the medium-and long-term investment horizons while it has positive effect in the short-term investment horizons. This finding may not be surprising given that much of the geopolitical instability with its associated risks historically emanate from the petroleum producing regions of the world like Middle East, West and North Africa. This result implies that geopolitical tension may generate diversification benefits between gold and oil assets, especially in medium- to long-runs, thus justifying the inclusion of geopolitical uncertainty shock in a pure oil asset portfolio.[5]

Table 7: Regression results on the effect of geopolitical risks

Series	Dependence	GPR	GPRA	GPRT
Returns	theta_s0RGL	-5.46E-05*** [-6.738]	-6.72E-06 [-1.261]	-4.67E-05*** [-5.851]
	theta_s1RGL	-5.90E-06*** [-5.304]	-7.99E-07 [-1.092]	-5.02E-06*** [-4.589]
D1	theta_s0N	3.83E-05*** [4.097]	3.40E-05*** [5.548]	8.81E-06 [0.961]
	theta_s1N	1.31E-05*** [3.002]	1.19E-05*** [4.163]	2.76E-06 [0.645]
D2	theta_s0N	1.09E-05*** [3.907]	5.05E-06** [2.752]	6.25E-06** [2.276]
	theta_s1N	4.50E-06*** [2.865]	1.11E-06 [1.076]	3.46E-06** [2.236]
D3	theta_s0N	3.04E-06 [0.166]	4.75E-05** [3.961]	-3.53E-05* [-1.966]
	theta_s1N	-2.88E-06 [-0.299]	2.21E-05*** [3.480]	-2.03E-05** [-2.139]
D4	theta_s0N	-9.49E-05*** [-3.172]	7.35E-07 [0.037]	-9.46E-05*** [-3.215]
	theta_s1N	-4.11E-05*** [-4.249]	-6.23E-06 [-0.980]	-3.52E-05*** [-3.700]
D5	theta_s0N	-2.52E-06 [-0.115]	4.93E-05*** [3.415]	-4.07E-05* [-1.886]
	theta_s1N	-8.82E-06 [-1.176]	8.31E-06* [1.686]	-1.43E-05* [-1.936]
D6	theta_s0N	-0.000166*** [-4.869]	-4.07E-05 [-1.816]	-0.000124*** [-3.701]
	theta_s1N	-3.75E-05*** [-6.747]	-7.61E-06** [-2.083]	-2.89E-05 [-5.291]
D7	theta_s0N	4.83E-05 [1.128]	-0.000118*** [-4.196]	0.000147*** [3.496]
	theta_s1N	1.33E-05* [1.785]	-4.25E-06 [-0.870]	1.69E-05** [2.311]
D8	theta_s0N	-0.000536*** [-10.903]	-1.98E-05 [-0.613]	-0.000492*** [-10.178]
	theta_s1N	-1.41E-05*** [-7.897]	-1.41E-06 [-1.209]	-1.20E-05*** [-6.883]

[5] Contagion can be defined as a rapid shock spillover that increases cross-market linkages (Forbes and Rigobon, 2002). Given this, we conducted additional analysis to deduce whether an increase in geopolitical risks also leads to a reduction in the possibility of contagion in the gold and oil markets via a decline in the correlation jumps. To obtain estimates of correlation jumps, we use 5-minute intraday log-returns data on gold and oil futures traded in NYMEX over a 24 hour trading day (pit and electronic). The futures price data, in continuous format, are obtained from www.disktrading.com and www.kibot.com, and covers the daily period of 9th December, 1997 to 26th May, 2017. Specifically, we compute three different types of correlation jumps, details of which have been presented in Appendix B (see equations A1, A2 and A3). As can be seen from Table B1 reported in the Appendix B of the paper, in general, GPR, GPRA and GPRT have a significant negative impact on the three correlation jumps estimates, and hence, tends to suggest that higher geopolitical risks reduces the possibility of contagion between these two important commodity markets, and in the process increases the possibility of diversification.

D9	theta_s0N	0.000451*** [6.199]	-0.000105** [-2.193]	0.000509*** [7.117]
	theta_s1N	8.26E-06*** [5.747]	-2.19E-06** [-2.325]	9.64E-06*** [6.830]
S9	theta_s0N	0.000507*** [10.740]	1.02E-05 [0.328]	0.000469*** [10.105]
	theta_s1N	0.000676*** [11.850]	-5.26E-05 [-1.405]	0.000684*** [12.202]

Note: ***, **, * denote, respectively, significance at the 1%, 5%, and 10% levels, with *t*-statistics in square brackets.

5. Conclusion

This paper investigated the time-varying dependence structure between gold and oil prices using daily data on gold prices and West Texas Intermediate Institute (WTI) crude oil spot prices covering from 2 January 1985 to 30 November 2017. Consequently, we make inference about the hedging and safe haven ability of gold for oil based on the results. Aside analysing the raw return series, we also capture heterogeneity among market participants by conducting the dependence analysis at different wavelet time scales. Further, motivated by extant literature that globalised markets respond to major political events, we investigated whether geopolitical risks can influence the dynamic dependence between gold and oil. We fitted several time invariant and time-varying copula models but conclude based on our results that the Rotated Gumbel and Normal time-varying Markov switching copula models respectively capture the features of our returns and wavelet series best. Our results vary depending on whether we consider the original return series or heterogeneous market participants. For example, gold has a good hedging ability for investors in the short- and medium-term horizons. However, it failed to compensate long-term investors against losses from oil price increase. Similarly, using the original series shows gold as a poor hedge. However, we provide evidence of gold's safe haven ability for oil thus, in extreme market conditions, gold represent a good diversification mechanism. On the influence of geopolitical risks, we found a statistically significant effect of this on the dynamic dependence between gold and oil returns and provide evidence of diversification benefits of geopolitical risks in the pure gold and oil asset portfolio.

The findings have important implications. From an academic perspective, an analysis based on time invariant or simple regime switching models will not capture well the best features of the gold-oil dependence structure and dynamics relative to the Markov switching copulas. Moreover, assuming that market agents are homogenous may be far from the reality. Therefore, any analysis of the relationship between oil and gold should consider these. From a practical perspective, these findings offer effective ways to help investors to manage their risks and improve their investment portfolio performance depending on their unique characteristics and investment time horizons. From a policy perspective, the regulation of the gold prices and management of oil prices by both the home and OPEC policy makers could be based on prudent discernment of the effects of oil price changes on the economy in general and the commodity market in particular. Risk management and portfolio diversification can become more effective if policy decisions incorporate the information related to the gold market and the heterogeneity of market agents. To avoid contagion effect especially in the short and medium term, there may be need for policy makers to put in place more effective financial control measures for monitoring cross-market co-movements.

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APPENDIX:

A. Coherency Analysis

Figure A1. Co-Spectral Analysis between Gold and Oil Log-Returns:

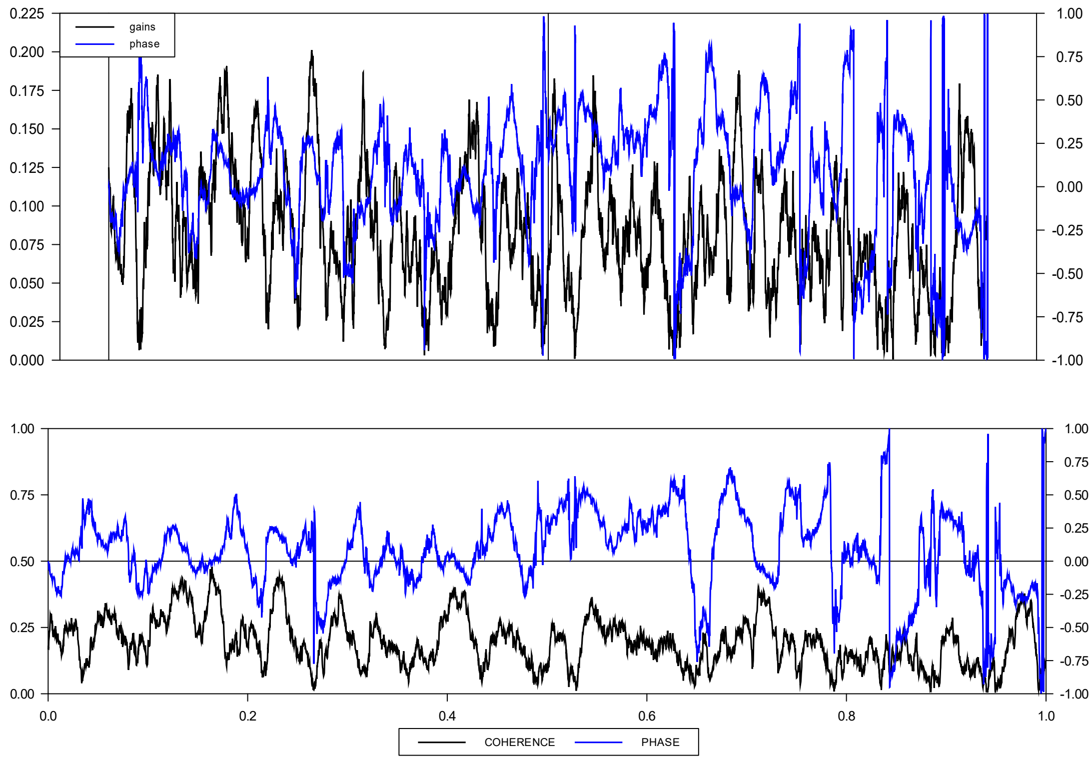
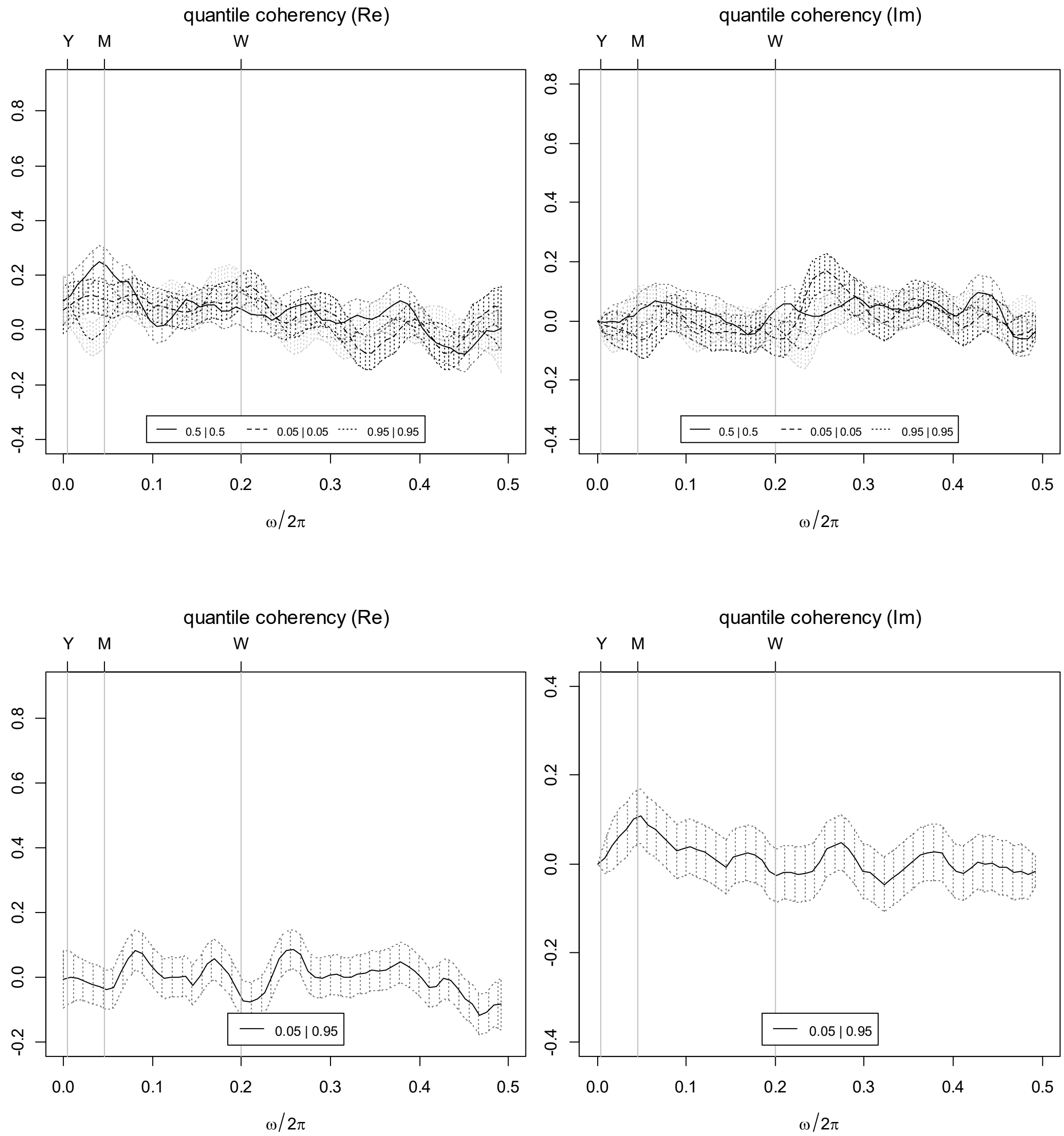


Figure A2. Quantile Coherency between Gold and Oil Log-Returns



B. Correlation Jumps

We estimate realized covariance and realized correlation non-parametrically, as introduced by Barndorff-Nielsen and Shephard (2004a):

$$RCov_t = \sum_{i=1}^{n} r_{a,i,t} \cdot r_{b,i,t}$$

In the absence of market microstructure noise, non-synchronicity of prices effect (Epps, 1979), and presence of jumps, the realized correlation coefficient adequately estimates correlation as follows:

$$RC_t = \frac{QCov_t}{\sqrt{QV_{a,t}}\sqrt{QV_{b,t}}} = \frac{RCov_t}{\sqrt{RV_{a,t}}\sqrt{RV_{b,t}}}$$

where $i = 1,...,n$ intraday high-frequency observations in day t, for the two assets a and b; while, RV_t stands for realized volatility $RV_t = \frac{1}{n}\sum_{i=1}^{n} r_{i,t}^2$.

Following Andersen et al., (2007), and Huang and Tauchen (2005), the correlation jump detection is similar to the volatility jump detection scheme, i.e., the difference between the realized correlation and the jump-free realized bipower-variation correlation (Barndorff-Nielsen and Shephard, 2004b):

$$J_t^{RC} = I\left[\max\left(|RC_t - RC_t^{BV}|,0\right) > c\right] \cdot \left(RC_t - RC_t^{BV}\right) \quad \text{(A1)}$$

where $RC_t^{BV} = \frac{RCov_t}{\sqrt{RV_{a,t}^{BV}}\sqrt{RV_{b,t}^{BV}}}$, $RV_t^{BV} = \mu_p^{-2}\sum_{i=2}^{n} |r_{i,t}| \cdot |r_{i-1,t}|$ is the realized bipower variation, and $\mu_p = E\left(|Z|^p\right)$ is the mean of the *p*-th absolute moment of a standard normal distribution. The continuous and jump component of realized correlation is: $JRC_t = RC_t - \max\left(|RC_t - RC_t^{BV}|,0\right)$ and $JRC_t = \max\left(|RC_t - RC_t^{BV}|,0\right)$, respectively.

$$J_t^{RCov} = I\left[\max\left(|RCov_t - RCov_t^{BV}|,0\right) > c\right] \cdot \left(RCov_t - RCov_t^{BV}\right) \quad \text{(A2)}$$

where $RCov_t^{BV} = \frac{\pi}{8}\sum_{i=2}^{n}\left|r_{(k)t,i} + r_{(q)t,i}\right| \cdot \left|r_{(k)t,i-1} + r_{(q)t,i-1}\right| - \left|r_{(k)t,i} - r_{(q)t,i}\right| \cdot \left|r_{(k)t,i-1} - r_{(q)t,i-1}\right|$ and $r_{(k)t,i}$ is the *k-th* component of the return vector $r_{i,t}$. We refer to the study of Barndorff-Nielsen and Shephard (2004a) regarding the $RCov_t^{BV}$.

$$J_t^{MRC} = I\left[\max\left(|RC_t - RC_t^{MRC}|,0\right) > c\right] \cdot \left(RC_t - RC_t^{MRC}\right) \quad \text{(A3)}$$

where $RC_t^{MRC} = \frac{RCov_t}{\sqrt{MRV_{a,t}}\sqrt{MRV_{b,t}}}$, $MRV_t = \frac{\pi}{6 - 4\sqrt{3} + \pi}\sum_{i=1}^{n} med\left(\left|r_{i-1,t}\right|,\left|r_{i,t}\right|,\left|r_{i+1,t}\right|\right)^2$ is median realized variance (Andersen et al., 2012).

Table B1. Impact of Geopolitical Risks on Correlation Jumps of Gold and Oil Log-Returns:

Correlation Jumps	GPR	GPRA	GPRT
J^{RC}	-9.37E-06 [-0.539]	6.99E-06 [0.439]	-6.03E-05*** [-4.635]
J^{RCOV}	-1.47E-07*** [-2.583]	-1.59E-07*** [-3.060]	2.59E-08 [0.607]
J^{MRC}	-1.98E-03*** [-2.848]	-1.81E-03*** [2.859]	-3.59E-04 [0.691]

Note: ***, **, * denote, respectively, significance at the 1%, 5%, and 10% levels, with *t*-statistics in square brackets.