Gold and Tail risks

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Highlights

- Own tail risk and oil tail risk predictability for gold returns is evaluated.
- Own tail risk has a negative effect while it is positive for oil tail risk.
- Higher out-of-sample forecast gains are realized with the tail risks.
- This outcome further supports the safe haven potential of gold.
- Several robustness tests conducted validate these conclusions.

Abstract

In this study, we consider as a predictor of gold return predictability, an alternative measure of systematic risk using the tail risk obtained from the four variants (Adaptive, Symmetric absolute value, Asymmetric slope and Indirect GARCH) of the Conditional Autoregressive Value at Risk (CAViaR) of Engle & Manganelli (2004). We conduct distinct analyses for the gold-tail risk nexus for both 1% and 5% VaRs across the in-sample and out-of-sample forecasts. The results of the in-sample predictability indicate contrasting effects of own tail risk and oil tail risk (a proxy for global risk factor) with negative and positive effects, respectively on gold returns reinforcing the safe haven property of the gold market against global risk. Evidence of the out-of-sample predictability supports the inclusion of both own tail risk and oil tail risk over the benchmark model and single-predictor (own tail risk) model for improved out-of-sample forecasts of gold returns. The results leading to these conclusions are robust to alternative proxies for oil price and magnitudes of VaR.

Keywords: Gold returns; Tail risks; Predictability; Forecast evaluation
JEL Codes: C22, C53, Q02

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1. Introduction

Motivation abounds around gold as a sought-after commodity for store of wealth purposes, as jewellery useful in the fashion industry, and as a financial asset useful for hedging/diversification benefits during turbulent times. We build the contribution for this study on the latter function, which highlights the importance of gold in providing protection against market risks (see Baur and Lucey, 2010; Beckmann et al., 2015; Gao and Bing, 2016; Dey and Sampath, 2018; Gkillas et al., 2020). Unlike previous studies, we explore the susceptibility of the gold market to tail risk (a measure of gold market systemic risk) amid other global financial market risks.[6] More specifically, we study the predictability of gold returns with own tail risk and global market tail risks measured with oil market tail risk. We hinge our contribution on the idea that tail risks embody rare (extreme) events that have been shown to matter in asset pricing models (see Barro, 2006; Huang et al., 2012; Van Oordt and Zhou, 2016). Before now, the idea is largely limited to the impacts of tail risks on equity markets returns[7] (see Kelly and Jiang, 2014; Bollerslev et al., 2015; Andersen et al., 2015; Vicente and Araujo, 2018; Chevapatrakul et al., 2019; Andersen et al., 2021).[8] Theoretically, we premise the linkage between gold returns and tail risk on the risk-return hypothesis in line with the Capital Asset Pricing Model (CAPM) pioneered by Sharpe (1964) and Lintner (1965) (see also, Merton (1980); Fama and French (2004)) and the Arbitrage Pricing Theory (APT) of Ross (1976). The former argues for the consideration of systemic (market) risk in the valuation of financial assets. While the former theory usually involves a single-factor model, the APT offers a broader perspective where multiple risk factors can be accommodated in the return predictability. Both theories are relevant to this study as we consider both the single-factor and multi-factor predictive models. In the case of the single-factor model, we consider (own) market risk measured as gold tail risk as the only factor in the predictive model for gold returns while the multi-factor model involves the consideration of both own market risk as well as other systemic risk measured as oil tail risk (the motivation for the consideration of oil tail risk is further discussed in this section). We expect that financial assets such as gold can produce higher returns and/or at least retain their

[6] This study improves on previous studies on the susceptibility of gold market to systemic risks by measuring market risk from the tail distribution of the gold return series unlike the body of literature which shop for proxies for the alternative market risks (see for example, Bekiros et al., 2017; Rehman et al., 2018; Salisu and Adediran, 2020).

[7] In addition, there are mixed findings which may interest studies on tail risks and stock markets (for example, Bali et al., 2009; Huang et al., 2012; DiTraglia and Gerlach, 2013; Kelly and Jiang, 2014; Bollerslev et al., 2015; Chen et al., 2018; Long et al., 2018; Baltussen et al., 2018).

[8] Lian et al. (2020) also document some findings for the impact of tail risk on the global oil market

value in the face of extreme risk; and thereby serve as good hedges. More often than not, risk-return expectation usually determines the direction of investment, especially in gold, given its established hedging and safe-haven advantages during market/extreme risk. In fact, this hypothesis usually forms the basis for the guidance investors receive from their advisors (Müller et al., 2011; Salisu et al., 2021).

Our focus on tail risks is relevant for investors in the global gold and related financial markets. During extreme market events which tail risk measures, investors are directly exposed to extreme losses which may pose challenges for the safe-haven property attributed to gold (see Long et al., 2019; Lin et al., 2019). Hence, findings from the predictability analysis of gold market returns using tail risks is relevant for hedging strategies and portfolio risk management especially since in extreme market scenarios, investors care more about minimising losses than taking more risks (see Reboredo et al., 2016; Mensi et al., 2017; Boako et al., 2019; Li, Guo and Li, 2021). We measure the tail risks following the Conditional Autoregressive Value at Risk (CAViaR) approach (see Engle and Manganelli, 2004).[9] This approach helps to quantify the potential loss on the given investment portfolio when exposed to downside or upside risk at certain confidence levels (95% and 99% in our case) (see Best, 2000; Yamai and Yoshiba, 2005; Straetmans et al., 2008; Acharya et al., 2017; Shahzad et al., 2018).

Our contribution is divided into two folds; one, the predictability of gold returns with own market risk and two, forecasting with global market risk measured as oil market tail risk. In particular, our interest in oil (as proxy for global market) is underscored by the established joint movements in gold and oil prices given their importance as strategic commodities, and that their price movements have important implications for the real economy and the financial markets (Reboredo, 2013). Similarly, the prices of the two commodities are capable of driving the prices of other commodities (Sari, Hammoudeh and Soytas, 2010; Dai et al., 2020). This joint movements became obvious from the beginning of 2000 through 2011 (see Reboredo, 2013). Meanwhile, the associated co-movement between the prices of the two commodities has been linked to the influence of oil price on global inflation. Evidence suggests that increase in oil price is capable of exacerbating inflation risk, thus eliciting the hedging potential of gold against inflation (Narayan,

[9] There are other measures of tail risks in the literature including co-skewness and co-kurtosis (see Dittmar, 2002), coexceedance measure (see Chiu et al., 2015), conditional value at risk (CoVaR) (see Tobias and Brunnermeier, 2016), among others.

Narayan and Zheng, 2010; Malliaris and Malliaris, 2013). Similarly, given the role of oil as an imperative input, a rise in its price could be growth retarding (Salisu, Gupta and Olaniran, 2021), and also cause reduction to prices of assets. Investors respond to this fundamental by exploring the store of value function of gold (Reboredo, 2013). More recently, researchers have engaged this cross-market information among markets as captured in investors' speculative sentiment (see Niu et al., 2022 on gold and stock market, and Luo et al., 2022 on gold and oil market) for predictability analyses. Our two contributions are firmly rooted in the extant literature for other financial markets (equities and oil markets) although yet to be explored for the gold market.[10] Hence, the study takes root in the literature that argues the predictive power of extreme market (tail) risks due to recurrence of risk-related extreme events such as the Global Financial Crisis, Asian Financial Crisis, European Sovereign Debt Crisis, BREXIT, COVID-19 pandemic that could increase correlations among assets and cut down on the number of risk takers in the markets (see Creti et. al., 2013; Shahzad et al., 2018; Long et al., 2019; Chevapatrakul et al., 2019; Li, Huang and Chen, 2021). In addition to these extreme events, facts are also available to show that factors such as geopolitical risks that affect global economic conditions and alter market sentiments may also drive gold market specific risks (see Li, Huang and Chen, 2021).[11]

On the second contribution, gold market risks can be traced to extreme risks/shocks transmitted from fellow financial markets. For this purpose, we obtain the tail risks for the global oil market in the predictive model. There are motivations for considering oil market tail risk as proxy for the global market risk. First, oil has over the years remain as a major source of energy required for the production of output and projected to contribute to 30% of global energy needs by year 2030 (see Salisu and Oloko, 2015). Second, there are evidences to show that international risk spillovers that are linked to prevailing market conditions or systemic risks may originate from the global oil market (see Martín-Barragán et al., 2015; Boldanov et al., 2016; Tiwari et al., 2018; Ji et al., 2020; Yin et al., 2021; Yang and Hamori, 2021).[12]

[10] A remotely related study on which the present builds is the paper of Wang et al. (2016) which is limited to extreme risk contagion among the four gold markets; namely the London, Shanghai, New York and Tokyo markets.

[11] Broadly speaking, geopolitical risks such as terrorist activities, political tensions, and threats of war, have been argued as sources of risk exposure to financial markets including equities, foreign exchange, and oil markets (see Noguera-Santaella, 2016; Antonakakis et al., 2017; Cheng and Chiu, 2018; Plakandaras et al., 2019; Jiang et al., 2020; Lee et al., 2021).

[12] Other remotely related findings show risk contagion from either or both oil and equity markets to gold (see for example, Junttila et al., 2018; Boako et al., 2019; Zhang and Liu, 2020; Lin et al., 2019) while others demonstrate close relations between the markets as alternative asset classes for diversification purposes (see Yao and Kuang, 2019; Roh et al., 2020; Tiwari et al., 2020).

The rest of the paper is structured as follows. Section 2 describes the detailed methodology with data issues. Section 3 discusses the results with the computation of the gold own tail and global market risks from the relevant returns series. Second 4 concludes the paper with implications for investment strategies.

2. Methodology and Data

2.1 Methodology

Our methodology is three-fold. First, we generate the tail risk data using the conditional autoregressive value at risk (CAViaR) which has four variants and therefore the need to use relevant diagnostics to determine the best fit tail risk among the competing variants becomes necessary. One of the attractions to the CAViaR approach of the Engle & Manganelli (2004) is that it concentrates on the asymptotic form of the tail, rather than modelling the whole distribution.[13] Second, we formulate a predictive model for gold return predictability based on the risk-return hypothesis (see Bowman, 1980; Fama & French, 2004; Kumar, 2016; among others) which captures the best fit tail risk data as a measure of systematic risk of the gold market. Third, we evaluate both the in-sample and out-of-sample predictability of the tail risks for gold returns using the Westerlund and Narayan (2012, 2015) approach which account other additional salient features of the predicator series. We proceed with the three steps as follows.

As regards the determination of the best fit tail risks, we consider a generic CAViaR specification given as[14]:

$$f_t(\beta) = \beta_0 + \sum_{i=1}^{q} \beta_i f_{t-i}(\beta) + \sum_{j=1}^{r} \beta_j l(x_{t-j}) \tag{1}$$

where $f_t(\beta) \equiv f_t(x_{t-1}, \beta_\theta)$ denote the time t θ-quantile of the distribution of portfolio returns formed at $t-1$. Note that θ subscript is supressed from β_θ as in equation (1) for notational convenience. Also, $p = q + r + 1$ is the dimension of β and l is a function of a finite number of

[13] Earlier approaches for modelling tail risks such as those developed by Boudoukh, Richardson & Whitelaw (1998) and Danielsson & De Vries (2000) are found not to be "extreme enough" in capturing the tail of the distribution, among other inherent shortcomings which the approach of Engle & Manganelli (2004) seeks to overcome.

[14] See Engle & Manganelli (2004) for technical details on the tail risk analysis. A recent application of this approach can be found in Salisu, Gupta and Ogbonna (2021) involving the tail risk predictability for stock returns of advance economies.

lagged values of observables. The autoregressive terms $\beta_i f_{t-i}(\beta)$, $i = 1,\ldots,q$, ensure that the quantile changes "smoothly" over time. The role of $l(x_{t-j})$ is to link $f_t(\beta)$ to observable variables that belong to the information set. The specifications for the four variants of the tail risks (that is, the Adaptive, Symmetric absolute value, Asymmetric slope and Indirect GARCH models) derived from equation (1) are respectively specified as follows:

Adaptive:

$$f_t(\beta_1) = f_{t-1}(\beta_1) + \beta_1 \left\{ \left[1 + \exp\left(G\left[y_{t-1} - f_{t-1}(\beta_1) \right] \right) \right]^{-1} - \theta \right\} \tag{2}$$

Symmetric absolute value:

$$f_t(\beta) = \beta_1 + \beta_2 f_{t-1}(\beta) + \beta_3 \left| y_{t-1} \right| \tag{3}$$

Asymmetric slope:

$$f_t(\beta) = \beta_1 + \beta_2 f_{t-1}(\beta) + \beta_3 (y_{t-1})^+ + \beta_4 (y_{t-1})^- \tag{4}$$

Indirect GARCH (1,1):

$$f_t(\beta) = \left(\beta_1 + \beta_2 f_{t-1}^2(\beta) + \beta_3 y_{t-1}^2 \right)^{1/2} \tag{5}$$

where G is some positive finite number which makes the model a smoothed version of a step function and the last term in equation (2) converges almost surely to $\beta_1 \left[I\left(y_{t-1} \le f_{t-1}(\beta_1) \right) - \theta \right]$ if $G \to \infty$ with $I(\cdot)$ representing the indicator function. Out of the four specifications, only equation (4) is asymmetric implying that the response to positive and negative returns is identical in this case while it differs for others. Note that the adaptive model has a unit coefficient on the lagged VaR, the other three are mean reverting implying that the coefficient on the lagged VaR is not constrained to be 1. Since only the best fit tail risk data among the four variants is used for the predictability analysis, we use the Dynamic Quantile test (DQ) test and %Hits[15] to determine the model that best fits the data.

On the second step, we use the best tail risk data as a predictor in the predictive model for gold return following the approach of Westerlund & Narayan (2012, 2015) method which

[15] These are standard test statistics for evaluating the relative performance of the alternative specifications of CAViaR test.

accommodates some other salient features such as persistence, endogeneity and conditional heteroscedasticity effects of the predictor series. Essentially, we construct two tail risk-based predictive models for gold returns: [16] The first model is a single-predictor model which only captures own (gold) tail risk as specified in equation (6):

$$gold_t = \alpha + \sum_{j=1}^{5} \beta_j tr_{t-j}^{gold} + \gamma \left(tr_t^{gold} - \rho_o tr_{t-1}^{gold} \right) + \varepsilon_t \tag{6}$$

where $gold_t$ is the log return of gold price at period t, computed as $100 * \Delta \log(p_t)$, p_t being the price data; α is the intercept; tr is the tail risk obtained as the one that best fits the data while ε_t is the zero mean idiosyncratic error term. Note that the coefficient β_j measures the relative impact of the own tail risk on stock returns and we allow for up to five lags given the data frequency (daily 5th-day of the week) as well as the need to capture more dynamics in the estimation process (Salisu, Akanni, & Raheem, 2020; Salisu, Raheem, and Eigbiremolen, 2020). Consequently, a joint (Wald) test with the null hypothesis - $\sum_{j=1}^{5} \beta_j = 0$ is carried out to test the predictability of own tail risk in equation (6). An additional term - $\gamma \left(tr_t^{gold} - \rho_o tr_{t-1}^{gold} \right)$ is included in the predictive model to resolve any inherent endogeneity bias as well as persistence effect. The choice of high (daily) frequency in this study requires that we further account for conditional heteroscedasticity effect which is implemented by pre-weighting equation (6) with the inverse of the standard deviation obtained from the conventional GARCH-type model and estimating the resulting equation with the Ordinary Least Squares to obtain the Feasible Quasi Generalized Least Squares estimates. The superscript on the tail risk term (tr) in equation (6) is used to indicate the return series used in computing the tail risk. In other words, the superscript "$gold$" implies that the gold return series is used for the tail risk in equation (6).

The second model extends equation (6) to include oil tail risk (see equation (7)) whose consideration can be motivated on two grounds. One, there is a body of literature suggesting a strong link between oil and gold given the safe haven property of the latter against the risk

[16] For computational details of this approach, see Westerlund and Narayan (2015) while useful applications are rendered in studies Bannigidadmath and Narayan (2015), Narayan and Bannigidadmath (2015), Narayan and Gupta (2015), Phan, Sharma, and Narayan (2015), Devpura, Narayan, and Sharma (2018), Salisu, Swaray and Oloko (2019), Salisu, Raheem and Ndako, 2019, among others).

associated with the former (see Zhang and Wei, 2010; Le and Chang, 2012; Shahbaz, Balcilar, and Ozdemir, 2017, among others) and second, oil risk can serve as a good proxy for global risk given its far-reaching influence on the global economy (see Stevens, 2016; Arezki et al., 2017).

$$\begin{aligned} gold_t = \alpha + \sum_{j=1}^{5} \beta_{1j} tr_{t-j}^{gold} + \gamma_1 \left(tr_t^{gold} - \rho_1 tr_{t-1}^{gold} \right) \\ + \sum_{j=1}^{5} \beta_{2j} tr_{t-j}^{oil} + \gamma_2 \left(tr_t^{oil} - \rho_2 tr_{t-1}^{oil} \right) + \varepsilon_t \end{aligned} \tag{7}$$

where all the variables, parameters and estimation procedure are as previously defined except that the additional terms, $\sum_{j=1}^{5} \beta_{2j} tr_{t-j}^{oil}$ and $\gamma_2 \left(tr_t^{oil} - \rho_2 tr_{t-1}^{oil} \right)$ are for the oil tail risk with the former used to evaluate the in-sample predictability of the oil tail risk and the latter to correct for any associated salient features as in the case of gold tail risk.

The third step involves the out-of-sample forecast evaluation of equations (6) and (7) relative to a benchmark (random walk) model that ignores the role of tail risks in the gold return predictability. A comparison of the two tail risk-based models is also considered to further examine whether the inclusion of oil tail risk in the gold return predictability would offer a higher predictive value over the own tail risk. Multiple out-of-sample forecast horizons involving 15, 30 and 60 days are evaluated using both the single (Root Mean Square Forecast Error) and pairwise (Clark & West (2007)) forecast measures while the 75:25 data split respectively for the sample estimation and out-of-sample predictability is adopted.[17]

2.2 Data and preliminary analyses

This study uses daily price series of gold, WTI and BRENT - both of which (the latter) are proxies for crude oil price. In order to ensure balanced series, the period covers 20/05/1987 to 22/02/2021, and they are obtained from Federal Reserve Economic Data [FRED][18]. The three series are

[17] Note that there is no theoretical guidance in the literature for data splitting in forecast analysis, however, studies have adopted 25:75, 50:50 and 75:25 respectively between the in-sample and out-of-sample forecasts (see Narayan and Gupta, 2015) and the outcome is observed to be insensitive to the choice of data split (see Narayan and Gupta, 2015; Salisu, Raheem, and Ndako, 2019; Salisu, Swaray and Oloko, 2019).

[18] https://fred.stlouisfed.org

converted into log returns in percentage, i.e., the first-difference of the natural logarithm of the indices multiplied by 100. It also employs USD/Pound exchange rates and US 3-months treasury bills (T-bills) rate as control variables.

The descriptive statistics for gold and oil price as well as their returns and the control variables are presented in Table 1. On the average, gold price has the highest price and returns, followed by BRENT. Measuring volatility in the market using standard deviation, the gold market has the highest volatility and this confirms while it has the highest returns judging by the mean value of its returns (0.0198). Similarly, all the series but WTI_R are positively skewed, while the kurtosis statistics suggests that all the series are platykurtic in their level form, as they are less than 3. However, all the series in their return form, are highly tailed given their leptokurtic nature. All this shows the non-normality nature of the series. In addition, the Jarque-Bera test equally lends credence to their non-normal as the normality assumption is rejected for all the series. Therefore, limiting the measurement of both the gold and crude oil markets to the distribution of the tail rather than the whole distribution is justified. Nonetheless, additional empirical results are offered in the succeeding section.

Moreover, figures 1&2 show the co-movement between the series, both in their level and return forms. What is obvious from figure 1 is that all the series have been moving in the same direction, until sometimes around 2015, when the co-movement breaks down.

Table 1: Summary statistics

	Mean	Std. Dev.	CV	Skewness	Kurtosis	JB test	Nobs
GOLD	750.7773	490.5739	65.3421	0.7255	2.0549	1100.591***	8809
GOLD_R	0.0198	0.9770	4941.9626	0.1770	12.5489	33509.44***	8808
WTI	45.2440	28.8025	63.6603	0.8419	2.6552	1084.209***	8809
WTI_R	0.0068	4.3593	64154.1722	-40.0426	2695.3410	2.66E+09***	8808
BRENT	46.4784	32.2647	69.4187	0.8846	2.6285	1199.406***	8809
BRENT_R	0.0450	2.4689	5488.8662	0.3013	53.5803	939053.8***	8808
USD/Pound	1.602	0.187	11.702	0.160	2.753	60.046***	8807
T-Bills	2.959	2.457	83.053	0.341	1.932	589.625***	8807

Note: Std. Dev. = Standard Deviation; CV = Coefficient of Variation; JB = Jarque-Bera; Nobs = Number of observations; *** denotes significance at 1% level. Return series are computed as $100 * \Delta \log\left(p_t\right)$, where p_t is the price.

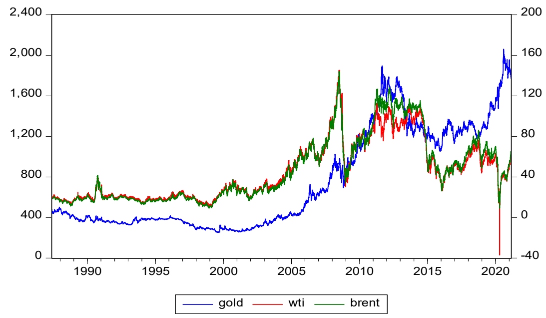

Figure 1: Co-movement of gold and oil prices

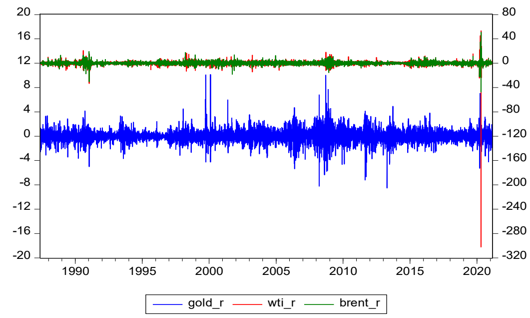

Figure 2: Co-movement of gold and oil return

In addition to the summary statistics offered above, we equally take a step forward to perform stationarity test to further justify our methodology. As detailed in Table 2, all the three test types used - Augmented Dickey-Fuller, Phillips-Perron and Kwiatkwoski-Phillips- Schmidt-Shin – support one another on the non-stationarity of all the price series at level. However, all the variables in their returns series are stationary at level, and at 1 percent significance level. In the same vein, when the difference of all the series (both at level and return form) are taken once, the stationarity tests show that all of them suffer no unit root, and they are all stationary at 1 percent significance level. Hence, the null hypothesis of unit-root (for both ADF and PP) is rejected at 1 percent level of significance for all of them. Similarly, the null hypothesis of stationarity for the KPSS cannot be rejected at the 1 percent level of significance for all the series in their first difference.

Table 2: Unit root/ Stationarity test

Variables	Level			First Difference		
	ADF	PP	KPSS	ADF	PP	KPSS
GOLD	0.2612	0.2886	9.7672***	-94.3912***	-94.4066***	0.2852
GOLD_R	-97.2427***	-97.2189***	0.4551*	-28.3667***	-1459.6750	0.0238
WTI	-1.8902	-1.9536	7.2928***	-75.2181***	-110.6325***	0.0435
WTI_R	-21.2148***	-75.6619***	0.2378	-29.0382***	-728.1984***	0.0084
BRENT	-1.6908	-1.8077	7.4483***	-90.0565***	-90.5007***	0.0508
BRENT_R	-68.3820***	-92.0259***	0.0409	-32.5762***	-2907.5700	0.0282
USD/Pound	-2.3949	-2.3714	2.9719***	-88.3400***	-88.3220***	0.0377
T-Bills	-1.0328	-0.8470	8.5674***	-14.5484***	-77.9824***	0.1075

Note: Unit-root and Stationarity tests are with constant and without deterministic trend. Lags are included with automatic and based on Schwarz info criterion. *, **, *** imply that the series is stationary at 1%, 5% and 10% respectively. ADF, PP and KPSS represent Augmented Dickey-Fuller, Phillips-Perron and Kwiatkwoski-Phillips-Schmidt-Shin Unit Root and stationarity tests respectively

3. The results

This section presents and discusses the result of our predictability and forecast performance. To choose the 'best" tail risk for each return series, having estimated the four CAViaR specifications described in the preceding section, we use the DQ test and %Hits to select the tail risk that best fits the return series being examined. The analyses are rendered for both 1% and 5% VaRs for robustness and the results are respectively presented in Tables 3, 4 and 5.[19] The decision rule is that %Hits should be relatively 1% for 1% VaR and 5% for 5% VaR while DQ test statistic should be significant. In cases, where more than one tail risk is statistically insignificant in terms of the DQ test, then, the tail risk with the closest value to the expected value for the % Hits is considered. Similarly, where all the tail risks are statistically significant, then, the %Hits becomes a major criterion except where some distinctions can still be made with the significant DQ test statistics. Thus, Tables 3, 4 and 5 summarize the results for the Symmetric Absolute Value (SAV), Asymmetric slope (ASY), Indirect GARCH (GARCH), and Adaptive (ADAPT) models for gold returns, Brent crude oil returns and WTI crude oil returns, respectively. For easy reference, the "best" choice for each commodity return series is put in bold and we find that the choice of VaR does not matter, as the performance seems not to differ between 1% VaR and 5% VaR. Thus, our out-of-sample forecast analysis is carried out for both VaRs in order to further test whether same conclusion would be obtained for the tail risks predictability. We also find that the return series for each of the commodities in their preferred model exhibit volatility, this is observable in the statistically significant coefficient (Beta2) on the autoregressive term. This further lends credence to the volatility clustering phenomenon as expressed in Engle and Manganelli (2004) with respect to tail risks (see also, Salisu, Gupta and Ogbonna, 2021). We provide graphical illustrations in Figures 1 and 2 for the 1% and 5% VaRs respectively and some relative co-movements can be teased out between the tail risks and the return series.

Furthermore, in our attempt to examine the predictive capability of market risks (tail risks) for gold returns, we present the result of our predictive model in Table 6. As earlier stated, we use the 'best' tail risk data as a predictor in the predictive model for gold return following the approach of Westerlund & Narayan (2012, 2015) and we construct two tail risk-based predictive models for gold returns, single predictor and multiple predictors (without and with control variables). The single predictor accommodates only own tail risk, while the multiple predictors accommodate both the own tail risk and oil risk, each at both 1% and 5% VaR. Consequently, Table 6 consists of two

[19] The computational and theoretical procedures for the implementation of the four variants of the CAViaR test are well presented in the Engle & & Manganelli (2004). We are also grateful to these authors for providing useful Matlab odes for CAViaR estimation.

panels – the first panel illustrating the relationship and predictability between the gold returns and various risk proxies at 1% VaR and the second panel showing the same but at 5% VaR. In the results, first, we examine the sole effect of the predictor, own tail risk, on gold returns. Expectedly, we find that own tail risk has a statistically significant negative relationship (at both 1% and 5% VaRs) with gold returns. In other words, the higher the prevalence of risks associated with the gold market, the less investors are willing to commit their investment into gold. Our results conform to those of Kelly and Jiang (2014) and Van Oordt and Zhou (2016). While the former also shows that tail risk has a strong predictive power for stock returns, Van Oordt and Zhou (2016) report that stocks with high tail betas suffer higher losses than those with relatively lower tail betas during a market crash.

Similarly, in the second model, on inclusion of oil risk (which measures the risk associated with the oil market), the negative relationship between gold and own tail risk remains unchanged (implying that the proposed predictive model is robust to alternative specifications). However, we find a positive relationship between gold returns and oil tail risk regardless of the choice of oil price proxy and Value-at-Risk. In addition to the robustness of the predictive model to alternative proxies for oil price, this outcome further corroborates the safe-haven property of gold against market risks (see also Baur and Lucey, 2010; Reboredo, 2013; Salisu, Raheem and Vo, 2021). These stances are unaffected by our inclusion of control variables. In other words, an increase in oil market risk tends to stimulate trading in the gold market particularly by investors seeking safe investments, thereby raising the demand for gold and by extension its prices as well as returns increase. Our findings have implications for investors and policy-makers. While gold can be a risky asset as suggest by its negative association with its own tail risk, its returns are usually independent of those of other assets, emphasising its hedging and safe-haven advantages as reported in our findings. Thus, investors seeking to minimise (maximise) their loss (profit) can observe the information provided by tail risks (both gold and oil) while making their investment decisions. Furthermore, since a proportion of country's foreign exchange reserves must be held in gold in order to act as a store of value, an assurance to fulfil debt obligations to depositors, note holders, trading partners, or to secure a currency (Reboredo, 2013), understanding the risk portends by gold market is important to guide the policy directions by monetary authorities, especially while using it to check inflation.

We then evaluated the forecast power of the tail risks for each of the models, focusing only on the out-of-sample periods. The sample is evaluated using two variants of the predictive model namely; one-predictor model (own tail risk) and multiple-predictor model (own tail risk and oil tail risk) without and with control variables. We subsequently analyse the sample at 1% and 5% VaRs and lastly, we spread our out-of-sample evaluation across multiple horizons (h = 15, 30 and 60 days), employing the Clark and West forecast method to evaluate the forecast performance. Three major findings standout from our results (see Table 7). One, the single predictor model with own tail risk fails to beat the random walk model. This result supports the findings by Díaz et al. (2020) who also report that random walk model out-performs the duo of random forest and gradient boosting models in forecasting copper prices. Two, the multiple predictor model outperforms the random walk model and by implication the single-predictor model. Accounting for control variables further improves the observed outperformance. Three, the results leading to the conclusions in one and two are robust to alternative proxies for oil price and magnitudes of VaR. Our further analysis to comparatively analyse the forecast prowess of both Brent and WTI suggests that the use of the latter may offer higher out-of-sample forecast gains than the former across all the horizons and at both 1% and 5% VaRs (see Table 8 showing lower RMSFE values for WTI than Brent in all the cases examined). This outcome validates the argument of Narayan and Gupta (2015) that the West Texas Intermediate crude oil price is a good reflector of movements in global oil prices.

Drawing from Liu et al. (2019), we further examine the economic significance of incorporating oil tail risk for prediction of gold returns, as a way to complement the statistical significance results from the Clark and West statistics. This allows us to ascertain the economic gains that oil tail risk as a predictor in our WN-type model yields for the prediction of gold returns over other contending models that do not incorporate oil tail risks. For a typical mean-variance utility investor, the goal is often to optimally allocate available shares among choice investments in contrast to a risk free asset (say, treasury bills rate); with a weight, w_t, defined as in equation (8):

$$w_t = \frac{1}{\gamma} \frac{\theta \hat{r}_{t+1} + (\theta - 1)\hat{r}^{f}_{t+1}}{\theta^2 \hat{\sigma}^2_{t+1}} \tag{8}$$

where γ is the risk aversion coefficient; θ is a leverage ratio that we set to 6 and 8, since investors are perceived to maintain an account margin of 10% (Zhang et al. 2018); $\hat{r}_{t+1}$ is the time $t+1$ stock returns forecast; $\hat{r}_{t+1}^{f}$ is a risk-free asset (three months Treasury bills' rate); and $\hat{\sigma}_{t+1}^{2}$ is 30-day moving average returns volatility estimate. The corresponding certainty equivalent return for the investors' optimal weight, w_t, is defined in equation (9)

$$CER = \bar{R}_p - 0.5(1/\gamma)\sigma_p^2 \tag{9}$$

where $\bar{R}_p$ is the out-of-sample period average portfolio returns $R_p = w\theta\left(r - r^f\right) + (1-w)r^f$; while σ_p^2 is the out-of-sample period portfolio returns' mean variance. For a given excess return volatility $\left(\sigma^2\right)$, the portfolio return variance is given as $Var\left(R_p\right) = w^2\theta^2\sigma^2$. The economic significance is determined by an objective utility maximization function given in equation (10)

$$\begin{aligned} U\left(R_p\right) &= E\left(R_p\right) - 0.5(1/\gamma)Var\left(R_p\right) \\ &= w\theta\left(r - r^f\right) + (1-w)r^f - 0.5(1/\gamma)w^2\theta^2\sigma^2 \end{aligned} \tag{10}$$

In reporting contending models' economic gains, we present estimates of the contending models' portfolio returns, volatilities, certainty equivalent returns and Sharpe ratios, $SP = \left(R_p - r^f\right)\Big/\sqrt{Var\left(R_p\right)}$. We adjudge a contending model as the one that yield the most economic gains if the model has the highest returns, CER and SP; and least volatility (see Liu et al., 2019). The economic significance result is presented in Table 9, with sub-groupings by leverage parameter (6 and 8), with 3 set as the risk aversion level.

Across the tail risks and oil proxies as well as model constructs, we find that high returns are associated with high risks; with pieces of evidence that reveal that incorporating oil tail risks, with or without accounting for control variables, does yield more economic gains than ignoring same. In most cases, accounting for control variables only yield a marginal economic gains. The stance is not markedly different for the different leverage ratios of 6 and 8, under the risk aversion of 3. Imperatively, oil tail risks is a relevant predictor for gold returns, given the satisfaction of the statistical and economic significance features. Conclusively, while incorporating oil tail risks in the predictive model for gold returns simultaneously improves forecast precision and yields some economic gains, controlling for other financial features enhances the predictability.

4. Conclusion

In this study, we consider as a predictor of gold return predictability, an alternative measure of systematic risk using the tail risk obtained from the four variants (Adaptive, Symmetric absolute value, Asymmetric slope and Indirect GARCH) of the Conditional Autoregressive Value at Risk (CAViaR) of Engle & Manganelli (2004). We conduct distinct analyses for the gold-tail risk nexus for both 1% and 5% VaRs across the in-sample and out-of-sample forecasts. We use the best tail risk data as a predictor in the predictive model for gold return following the approach of Westerlund & Narayan (2012, 2015) and we construct two tail risk-based predictive models for gold returns, single predictor and multiple predictors. The single predictor accommodates only own tail risk, while the multiple predictors accommodate both the own tail risk and oil risk, each at both 1% and 5% VaR. For the single predictor model, we find that own tail risk has a significant negative relationship (at both 1% and 5% VaRs) with gold while the multiple predictor model retains upholds the latter, it however shows a significant positive relationship between gold returns and oil tail risk, thus, confirming the safe-haven potential of gold. In addition, the out-of-sample forecast analysis supports the inclusion of both own tail risk and oil tail risk in the predictive model of gold returns as the multi-predictor model outperforms the benchmark model as well as single-predictor (own tail risk) model while the WTI crude oil price offers higher out-of-sample forecast gains than the Brent crude oil price. Oil tail risks does yield economic gains for modelling gold returns. The results leading to these conclusions are robust to alternative magnitudes of VaR and multiple forecast horizons.

As a policy recommendation, understanding the source of risk (either from gold or oil) is essential while formulating policies, especially the ones that relate to inflation hedging. Our results would also prove useful to a profit-maximising investors. For generalization of our results, consideration for the nexus between tail risks of other precious metals and their returns is delayed for further studies. Similarly, further research is also suggested for threshold analysis of tail risks. That is, how extreme should tail risk be before yielding negative return. This is necessary to provide more explanation for risk-return paradox observed in our results.

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Table 3: Estimates and Relevant statistics for the CAViaR specification of gold returns

	SAV		**ASY**		**GARCH**		**ADAPTIVE**	
Gold	**1%**	**5%**	**1%**	**5%**	**1%**	**5%**	**1%**	**5%**
Beta1	0.1410	0.0743	**0.0562**	**0.0217**	0.0683	0.0205	0.7400	0.3610
Standard errors	0.0291	0.0096	**0.0320**	**0.0112**	0.0384	0.0068	0.0793	0.0437
P values	0.0000	0.0000	**0.0396**	**0.0265**	0.0375	0.0014	0.0000	0.0000
Beta2	0.9120	0.9090	**0.9110**	**0.9020**	0.9380	0.9100		
Standard errors	0.0146	0.0074	**0.0255**	**0.0129**	0.0082	0.0052		
P values	0.0000	0.0000	**0.0000**	**0.0000**	0.0000	0.0000		
Beta3	0.2320	0.1890	**0.2120**	**0.1740**	0.3220	0.1980		
Standard errors	0.0202	0.0064	**0.1000**	**0.0152**	0.1670	0.0354		
P values	0.0000	0.0000	**0.0171**	**0.0000**	0.0271	0.0000		
Beta4			**0.2200**	**0.1750**				
Standard errors			**0.0940**	**0.0248**				
P values			**0.0096**	**0.0000**				
RQ	247.0000	797.0000	**244.0000**	**794.0000**	243.0000	791.0000	268.0000	834.0000
Hits in-sample (%)	1.0100	5.0300	**0.9990**	**5.0100**	1.0100	5.0600	0.8970	4.5000
Hits out-of-sample (%)	0.6000	4.5000	**0.9000**	**4.5000**	0.8000	4.9000	1.0000	4.9000
DQ in-sample (P-values)	0.1410	0.2080	**0.6240**	**0.2720**	0.3800	0.2330	0.5110	0.0143
DQ out-of-sample (P-values)	0.6080	0.7960	**0.9250**	**0.9620**	0.9740	0.8890	0.1790	0.0112

Note: SAV = Symmetric Absolute Value; ASY = Asymmetric slope; GARCH = Indirect GARCH; ADAPT = Adaptive. The tail risk that best "fits" the return series is put in bold. The criteria used are the DQ test and %Hits for Out-of-Sample. For the "best" tail risk variant, we expect the %Hits to be 1% for 1% VaR and 5% for 5% VaR while DQ test statistic is not expected to be significant. In cases, where more than one tail risk is statistically insignificant in terms of the DQ test, then, we consider the tail risk with the closest value to the expected value for the % Hits. In the same vein, where all the tail risks are statistically significant, then, the %Hits becomes a major criterion except where some distinctions can still be made with the significant DQ test statistics.

Table 4: Estimates and Relevant statistics for the CAViaR specification of oil (Brent) returns

	SAV		ASY		GARCH		ADAPTIVE	
Brent	**1%**	**5%**	**1%**	**5%**	**1%**	**5%**	**1%**	**5%**
Beta1	0.1840	0.1370	0.0561	0.0758	**0.4130**	**0.2730**	1.0800	0.3800
Standard errors	0.0757	0.0357	0.0254	0.0217	**0.1110**	**0.0852**	0.0446	0.0291
P values	0.0076	0.0001	0.0135	0.0002	**0.0001**	**0.0007**	0.0000	0.0000
Beta2	0.9080	0.9130	0.9230	0.9190	**0.8710**	**0.8990**		
Standard errors	0.0459	0.0260	0.0241	0.0169	**0.0047**	**0.0104**		
P values	0.0000	0.0000	0.0000	0.0000	**0.0000**	**0.0000**		
Beta3	0.2740	0.1380	0.2180	0.0903	**0.8410**	**0.2040**		
Standard errors	0.1360	0.0383	0.0932	0.0322	**0.3250**	**0.2070**		
P values	0.0217	0.0002	0.0097	0.0025	**0.0048**	**0.1620**		
Beta4			0.2350	0.1630				
Standard errors			0.0795	0.0292				
P values			0.0015	0.0000				
RQ	541.0000	1810.0000	540.0000	1800.0000	**533.0000**	**1810.0000**	601.0000	1850.0000
Hits in-sample (%)	0.9990	4.9900	1.0100	4.9900	**0.9860**	**5.0500**	0.9860	4.9300
Hits out-of-sample (%)	1.6000	5.6000	1.6000	5.8000	**1.2000**	**5.7000**	1.8000	5.3000
DQ in-sample (P-values)	0.2340	0.0253	0.2630	0.1090	**0.5610**	**0.0565**	0.0070	0.3450
DQ out-of-sample (P-values)	0.0985	0.0373	0.1070	0.0426	**0.2950**	**0.2680**	0.0000	0.0000

Note: SAV = Symmetric Absolute Value; ASY = Asymmetric slope; GARCH = Indirect GARCH; ADAPT = Adaptive. The tail risk that best "fits" the return series is put in bold. The criteria used are the DQ test and %Hits for Out-of-Sample. For the "best" tail risk variant, we expect the %Hits to be 1% for 1% VaR and 5% for 5% VaR while DQ test statistic is not expected to be significant. In cases, where more than one tail risk is statistically insignificant in terms of the DQ test, then, we consider the tail risk with the closest value to the expected value for the % Hits. In the same vein, where all the tail risks are statistically significant, then, the %Hits becomes a major criterion except where some distinctions can still be made with the significant DQ test statistics.

Table 5: Estimates and Relevant statistics for the CAViaR specification of oil (WTI) returns

	SAV		**ASY**		**GARCH**		**ADAPTIVE**	
WTI	**1%**	**5%**	**1%**	**5%**	**1%**	**5%**	**1%**	**5%**
Beta1	0.1730	0.1610	0.0791	0.0880	**0.9650**	**0.4210**	1.1300	0.8330
Standard errors	0.0604	0.0207	0.0543	0.0285	**0.5070**	**0.0583**	0.1300	0.0227
P values	0.0021	0.0000	0.0724	0.0010	**0.0286**	**0.0000**	0.0000	0.0000
Beta2	0.9150	0.8930	0.9120	0.8980	**0.8530**	**0.8690**		
Standard errors	0.0143	0.0199	0.0153	0.0246	**0.0251**	**0.0049**		
P values	0.0000	0.0000	0.0000	0.0000	**0.0000**	**0.0000**		
Beta3	0.2650	0.1780	0.2950	0.1600	**0.8110**	**0.2500**		
Standard errors	0.0180	0.0372	0.0347	0.0722	**0.1460**	**0.0420**		
P values	0.0000	0.0000	0.0000	0.0134	**0.0000**	**0.0000**		
Beta4			0.2230	0.1670				
Standard errors			0.0239	0.0444				
P values			0.0000	0.0001				
RQ	581.0000	1930.0000	583.0000	1940.0000	**586.0000**	**1940.0000**	674.0000	2010.0000
Hits in-sample (%)	0.9860	4.9900	1.0200	4.9900	**1.0200**	**5.0100**	0.9990	4.9700
Hits out-of-sample (%)	1.6000	6.8000	1.7000	6.7000	**1.4000**	**6.0000**	1.7000	5.0000
DQ in-sample (P-values)	0.5770	0.0904	0.0723	0.0037	**0.9110**	**0.0147**	0.0554	0.0849
DQ out-of-sample (P-values)	0.0001	0.0055	0.0001	0.0050	**0.2800**	**0.0534**	0.0000	0.0001

Note: SAV = Symmetric Absolute Value; ASY = Asymmetric slope; GARCH = Indirect GARCH; ADAPT = Adaptive. The tail risk that best "fits" the return series is put in bold. The criteria used are the DQ test and %Hits for Out-of-Sample. For the "best" tail risk variant, we expect the %Hits to be 1% for 1% VaR and 5% for 5% VaR while DQ test statistic is not expected to be significant. In cases, where more than one tail risk is statistically insignificant in terms of the DQ test, then, we consider the tail risk with the closest value to the expected value for the % Hits. In the same vein, where all the tail risks are statistically significant, then, the %Hits becomes a major criterion except where some distinctions can still be made with the significant DQ test statistics.

Fig. 3: Co-movement between commodity returns and tail risk of 1 percent VaR

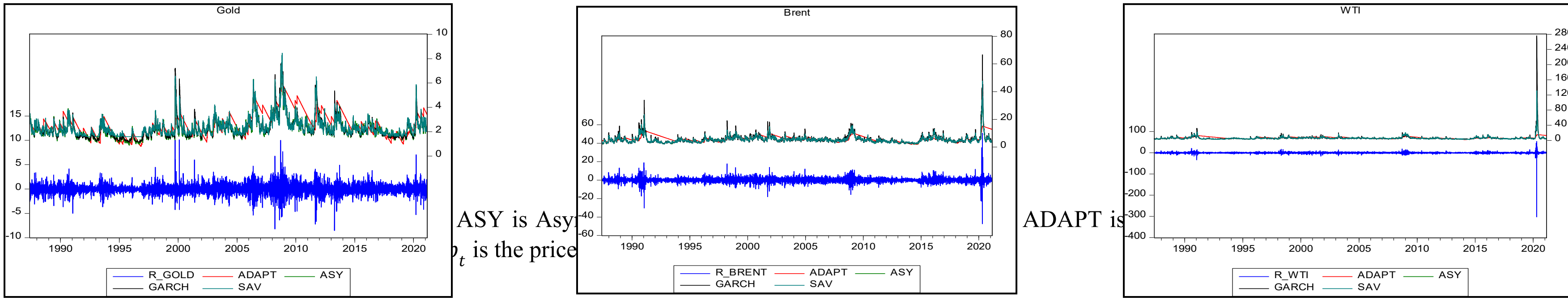

Fig. 4: Co-movement between commodity returns and tail risk of 5 percent VaR

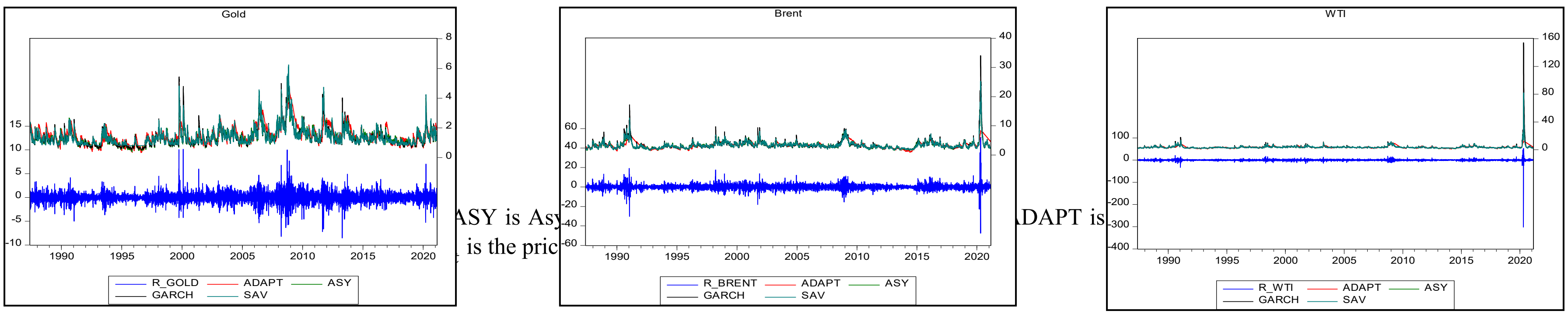

Table 6: Predictability result for gold and oil returns

	Single Predictor	Multiple Predictors							
		Without Control Variables				With Control Variables			
	Gold TR	Gold TR	Brent TR	Gold TR	WTI TR	Gold TR	Brent TR	Gold TR	WTI TR
1%	-0.1017[a]	-0.1941[a]	0.0450[a]	-0.1586[a]	0.0323[a]	-0.2321[a]	0.0406[a]	-0.1903[a]	0.02670[a]
	(0.0300)	(0.0304)	(0.0094)	(0.0307)	(0.0049)	(0.0300)	(0.0092)	(0.0303)	(0.0048)
	[11.5312]	[40.7340]	[23.0810]	[26.7674]	[44.1342]	[59.6869]	[19.3561]	[39.3852]	[31.7227]
5%	-0.1319[a]	-0.2562[a]	0.0987[a]	-0.2101[a]	0.0552[a]	-0.3073[a]	0.0897[a]	-0.2520[a]	0.0459[a]
	(0.0406)	(0.0412)	(0.0179)	(0.0416)	(0.0083)	(0.0407)	(0.0177)	(0.0410)	(0.0082)
	[10.5440]	[38.7137]	[30.2962]	[25.5585]	[43.7656]	[57.0970]	[25.7992]	[37.6249]	[31.2182]

Note: TR=Tail risk. Single predictor here only accommodates own tail risk while Multiple predictors involve both own and oil tail risks. Values in parenthesis denote standard errors, while those in square brackets represent F-statistics. 1% and 5% denote 1% and 5% VaRs, respectively. [a, b, c] represent 1%, 5% and 10% level of significance respectively.

Table 7: Out-of-sample forecast evaluation result

	SPM versus RWM	MPWOCVM versus RWM		SPM versus MPWOCVM		MPWCVM versus MPWOCVM	
	Gold TR	Gold/ Brent TR	Gold/ WTI TR	Gold/ Brent TR	Gold/ WTI TR	Gold/ Brent TR	Gold/ WTI TR
1% 15	-0.0015	0.0680[a]	0.0072	0.0351[c]	0.0333[c]	0.1810[a]	0.2784[a]
	(-0.0620)	(2.0636)	(0.2610)	(1.4288)	(1.3583)	(7.2430)	(9.2830)
30	-0.0021	0.0677	0.0068	0.0345[c]	0.0327[c]	0.1805[a]	0.2777[a]
	(-0.0877)	(0.0713)	(0.2490)	(1.4056)	(1.3348)	(7.2397)	(9.2810)
60	-0.0018	2.1378	0.0069	0.0348[c]	0.0330[c]	0.1808[a]	0.2776[a]
	(-0.0752)	(0.0711)	(0.2522)	(1.4245)	(1.3532)	(7.2803)	(9.3174)
5% 15	-0.0008	2.1367	0.0083	0.0359[c]	0.0355[c]	0.1801[a]	0.2862[a]
	(-0.0318)	(0.0709)	(0.3028)	(1.4455)	(1.4326)	(7.1983)	(9.2280)
30	-0.0014	2.1395[a]	0.0080	0.0352[c]	0.0348[c]	0.1796[a]	0.2855[a]
	(-0.0575)	(2.0593)	(0.2898)	(1.4222)	(1.4091)	(7.1953)	(9.2259)
60	-0.0011	0.0675[a]	0.0080	0.0355[c]	0.0351[c]	0.1799[a]	0.2853[a]
	(-0.0455)	(2.0630)	(0.2931)	(1.4405)	(1.4271)	(7.2372)	(9.2610)

Note: SPM – Single Predictor Model; RWM – Random Walk Model; MPWCVM – Multiple Predictor with Control Variable Model; and MPWOCVM – Multiple Predictor without Control Variable Model. For the Clark & West test, the null hypothesis of equal forecast accuracy between the benchmark and the proposed models is rejected if the t-statistic is greater than +1.282 (for a one sided 0.10 test), +1.645 (for a one sided 0.05 test), and +2.00 for 0.01 test (for a one sided 0.01 test) (see Clark & West, 2007), and are denoted by [c, b] and [a], respectively; and the values of the t-statistic are denoted in parentheses. CW denotes Clark and West (2007) test. For the comparison of a single-predictor model with the multiple-predictor model, a rejection of the null hypothesis implies the superior out-of-sample forecast performance of the latter over the former while a non-rejection implies equal forecast accuracy between the two models. Single predictor here only accommodates own tail while multiple predictors involve both own and oil tail risks. Values in parenthesis represents t-statistics.

Table 8: Root Mean Square Forecast Error for the Oil proxies

RMSFE	1% VaR			5% VaR		
	15	30	60	15	30	60
Multiple Predictor with Control Variable Model						
Brent TR	1.4091	1.4081	1.4064	1.3930	1.3921	1.3904
WTI TR	1.3352	1.3344	1.3328	1.3362	1.3353	1.3337
Multiple Predictor without Control Variable Model						
Brent TR	1.4732	1.4723	1.4702	1.4593	1.4583	1.4562
WTI TR	1.3756	1.3748	1.3729	1.3729	1.3721	1.3701

Note: TR=Tail risk. The RMSFE values presented here are for the multi-predictor models where both gold and oil tail risks serve as predictors. VaR=Value-at-Risk.

Table 9: Economic Significance

Model	Returns	Volatility	CER	SP	Returns	Volatility	CER	SP
	$\gamma = 3$ and $\theta = 6$				$\gamma = 3$ and $\theta = 8$			
Brent								
1 per cent VaR								
RWM	-8.39E+30	1.21E+32	-8.39E+30	-7.64E+14	-8.25E+30	1.29E+32	-8.25E+30	-7.25E+14
SPM	0.4320	11.0084	0.3986	**0.1090**	0.4373	11.0694	0.4038	**0.1102**
MPWOCVM	0.2343	8.6161	0.2001	**0.0558**	0.2380	8.6623	0.2038	**0.0569**
MPWCVM	0.1655	6.4711	0.1133	**0.0373**	0.1674	6.4952	0.1152	**0.0380**
5 per cent VaR								
RWM	-8.39E+30	1.21E+32	-8.39E+30	-7.64E+14	-8.25E+30	1.29E+32	-8.25E+30	-7.25E+14
SPM	0.4263	10.9823	0.3958	**0.1074**	0.4318	11.0460	0.4012	**0.1087**
MPWOCVM	0.2374	8.7634	0.2052	**0.0564**	0.2411	8.8110	0.2090	**0.0575**
MPWCVM	0.1826	6.4119	0.1322	**0.0443**	0.1844	6.4357	0.1340	**0.0449**
WTI								
1 per cent VaR								
RWM	-8.39E+30	1.21E+32	-8.39E+30	-7.64E+14	-8.25E+30	1.29E+32	-8.25E+30	-7.25E+14
SPM	0.4320	11.0084	0.3986	**0.1090**	0.4373	11.0694	0.4038	**0.1102**
MPWOCVM	0.0550	6.9724	0.0229	**-0.0058**	0.0574	7.0050	0.0252	**-0.0050**
MPWCVM	0.1484	5.8205	0.1003	**0.0323**	0.1496	5.8384	0.1014	**0.0327**
5 per cent VaR								
RWM	-8.39E+30	1.21E+32	-8.39E+30	-7.64E+14	-8.25E+30	1.29E+32	-8.25E+30	-7.25E+14
SPM	0.4328	11.0361	0.3994	**0.1091**	0.4381	11.0971	0.4047	**0.1103**
MPWOCVM	0.0639	7.0112	0.0316	**-0.0025**	0.0663	7.0443	0.0340	**-0.0016**
MPWCVM	0.1576	5.8609	0.1112	**0.0360**	0.1588	5.8795	0.1124	**0.0364**

Note: SPM – Single Predictor Model; RWM – Random Walk Model; MPWCVM – Multiple Predictor with Control Variable Model; and MPWOCVM – Multiple Predictor without Control Variable Model. Value in bold fonts indicate cases where the corresponding model yields more economic gains than the RWM.