Oil tail risk and the tail risk of the US Dollar Exchange rates

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Highlights

- The predictive value of oil tail risk for the tail risk of US Dollar exchange rates is evaluated.
- The conditional autoregressive value at risk (CAViaR) is used to estimate the tail risks under 1% and 5% VaRs.
- The analysis is conducted for USD/CAD, USD/GBP and USD/JPY for both the in-sample and out-of-sample forecasts.
- The relationship is positive for USD/CAD, USD/GBP while it is negative for USD/JPY albeit at 5% VaR.
- Oil market risk causes instabilities in USD/CAD and USD/GBP while USD/JPY can be used to hedge against such instabilities.

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Abstract[6]

This study tests both the in-sample and out-of-sample predictive value of oil tail risk for the tail risk of US Dollar exchange rates (USD/CAD, USD/GBP and USD/JPY), where the conditional autoregressive value at risk (CAViaR) of the Engle & Manganelli (2004) is used to estimate the tail risks under 1% and 5% VaRs. Thereafter, we construct a predictive model using the best fit tail risks while the predictive value of the oil tail risk is evaluated for both the in-sample and out-of-sample forecasts. We find evidence of a positive association between the oil tail risk and the USD tail risks when the USD/CAD, USD/GBP are considered, where downtowns in the oil markets are capable of causing instabilities in the U.S. foreign exchange market while it is negative for USD/JPY albeit at 5% VaR, suggesting the safe haven property of the latter during oil crisis. Accounting for the dynamics of oil tail risk in the predictive model of the tail risks of USD exchange rates improves both the in-sample and out-of-sample forecasts and the outcome leading to these conclusions is insensitive to the choice of oil price proxy and the magnitude of VaR.

Keywords: Tail risks; Oil market, US/GBP; Predictability; Forecast evaluation
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1. Introduction

The interconnectedness between the US Dollar and the crude oil market has been like that of a Siamese twin. On one hand, the US Dollar is the most used legal tender for international crude oil trading, thus the fluctuation in US Dollar exchange rate has a way of prompting the volatility of crude oil price (Zhang et al., 2008). Put differently, movements in the value of US Dollar have been associated with the way oil is being priced. Specifically, US Dollar depreciation has been very key in driving up crude oil price (see Zhang et al., 2008). Similarly, the US Dollar remains the world legal tender (see Seetharaman et al., 2017), hence its connection with oil price, which is a global factor capable of influencing the level of real economic activity in a large open economy like the U.S., is worth investigating.

While there are many studies on oil market volatility and the risk it portends to investors (see for example, Salisu and Fasanya, 2013; Salisu and Mobalaji, 2013; Khalfaoui, Boutahar and Boubaker, 2015; Mensi et al., 2017; Ji, Liu and Fan, 2019; Jie, Huang and Ping, 2021, Salisu et al., 2021a), exchange rate volatility could also affect the way investors make their investment choices[7]. This is especially so, if the exchange rate movements are not fully predictable.

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[7] Since the US Dollar is the leading reserve and the foremost intervention currency in the world, the extent to which other major exchange rates respond to its asymmetric behaviour is of great importance to investors (Laopodis, 1997).

Dell'Ariccia (1999) notes that risk associated with exchange rate volatility may cause a risk-averse investor to reduce or diversify their investment portfolio to a less risky one in the domestic market. Moreover, following the seminal work of Meese and Rogoff (1983a, 1983b) on the failure of standard models that relate exchange rates to monetary variables to beat the random walk, concerted efforts have been made to show the predictability of exchange rates by some macroeconomic fundamentals in recent times (see Engel et al., 2007; Moosa, 2013; Moosa and Burns, 2014a, 2014b; Wen et al., 2018; Baku, 2019; Ren, Wang and Zhang, 2019; Salisu et al., 2019a, 2019b; Salisu et al., 2020). Essentially, there is evidence that these fundamentals (especially oil) have some predictive contents for future exchange rate. However, what remains relatively new in the literature relates to the role of the extreme risks in the predictability analysis. In other words, rather than using the actual series for the predicted and the predictand, the extreme risks series are used. The departure from the extant literature that focused on returns (see for example, Salisu and Mobolaji, 2013; Salisu et al., 2020, among others) to adopting tail risks associated with the two markets is by way of appropriately representing the realities of the markets. This is premised on the fact that the tail information, rather than returns, reveal the possible risks associated with markets and understanding the nexus between the compared markets could better equip investors to make informed decisions when confronted with alternative investment options in the presence of risks. Exploiting the information contained in the tail risks tends to improve the forecastability of the return series (see for example, Ogbonna and Olubusoye, 2021; Salisu et al., 2021b, among others). From investors' perspective, the consideration of extreme risks is crucial when making investment decisions as these risks usually have bad outcomes or high consequences when they occur and therefore exploiting their information when analyzing return series would offer more robust information to profit maximizing investors when making investment decisions.

Thus, our study attempts to examine the predictive value of oil market tail risk, being a global measure of systematic risk, for the tail risk of exchange rate returns, focusing on the US Dollar whose risk tends to have greater spillover effects globally than other convertible currencies. While we recognize that there are a number of theories[8] that have been used to validate exchange rate behaviour under different market conditions, this study is hinged on the theory of exchange rate determination based on imperfect financial market proposed by Gabaix and Maggiori (2015).

[8] These theories range from uncovered interest rate parity, purchasing power parity, Dornbursch overshooting theory, capital asset pricing model, among others.

They posit that capital flows impact exchange rates by influencing the balance sheets of investors who bear the risks associated with foreign demand imbalances for financial assets. These changes to their balance sheets make investors to change their required compensation for holding currency risk, thus affecting both the level and volatility of exchange rates.

Our contribution is twofold: (i) we examine the predictability of US Dollar tail risk with oil tail risk; and (ii) we establish the out-of-sample forecast prowess of oil tail risk for US Dollar tail risk. Some theoretical considerations for linking foreign exchange risk to oil tail risk are provided in the next succeeding section of the paper (see also, Salisu et al., 2020).

In addition, attempts have been made to study the predictive content of tail risk for some macroeconomic fundamentals (see Andersen et al., 2015; Vicente and Araujo, 2018; Chevapatrakul et al., 2019; Andersen et al., 2020; Lian et al., 2020; Gupta et al., 2021; Salisu et al., 2021a, 2021b). We aim to extend these plethora of studies on the predictability of exchange rate returns based on information content of oil tail risks while the focus is on U.S. Dollar exchange rates in which the British pound sterling (GBP), Japanese Yen (JPY) and the Canadian Dollar (CAD) serve as the reference currencies. We do this, considering the strength of trade relations that exist between the United States and some of these countries (among the G7 countries with long range of high frequency dataset[9]).

At this point, it is worth noting that there are primarily two approaches to computing tail risks, one that is associated with option implied metrics, and the other which is based on underlying returns data (Kelly and Jiang, 2014). Since such a long period of historical data on options is unavailable, we opt for the second alternative, in which we estimate tail risk using Value at Risk (VaR) by employing conditional autoregressive VaR (CAViaR) specifications, in consonance with Engle and Manganelli (2004). While a more detailed computational advantages of using the CAViaR approach is well documented in Engle and Manganelli (2004), it is noteworthy to highlight that the CAViaR helps to overcome the statistical problem inherent in the standard VaR method. Since VaR is simply a particular quantile of future portfolio values, conditional on current information, and because the distribution of portfolio returns typically changes over time, the challenge is to find a suitable model for time-varying conditional quantiles, an issue that is ignored in the standard VaR but incorporated in the CAViaR (Salisu et al., 2021b).

[9] The Euro currency is excluded as it was launched in 1999 while those of Canadian Dollar, Japanese Yen and British pound sterling have high (daily) frequency data dated back to 1971.

There are other approaches of modelling tail risks (see Boudoukh, Richardson and Whitelaw, 1998; Danielsson and de Vries, 2000), however we favour the one proposed by Engle and Manganelli (2004) given the inherent shortcomings in the previous approaches and the ability of the latter to overcome them. For instance, the approach proposed by Danielsson and de Vries (2000) is not "extreme enough” to capture the tail of the distribution and more importantly, the quantile models are nested in a framework of iid variables, which is not consistent with the characteristics of most financial series, and, consequently, the risk of a portfolio may not vary with the conditioning information set (Engle and Manganelli, 2004; Salisu et al., 2021b). For this reason, the models considered are: (i) the adaptive model, (ii) the symmetric slope model, (iii) the asymmetric slope model, and (iv) the indirect generalized autoregressive conditional heteroscedasticity (GARCH) model with an autoregressive mean. Then, the specific tail risks model that best fits the exchange rate returns data statistically, is employed to forecast exchange rate returns based on an out-of-sample forecasting exercise, given that the ultimate test of any predictive model (in terms of the econometric methodologies and the predictors adopted) is in its forecasting performance (Campbell, 2008).

Our results show that the tail risks of two out of the three USD currency pairs considered, USD/GBP and USD/CAD, have a strong positive connection with oil tail risk for both 1% and 5% VaRs and irrespective of the choice of oil price proxy. This indicates that downtowns in the oil markets are capable of causing instabilities in the U.S. foreign exchange market. For USD/JPY, the result is in sharp contrast with those of USD/GBP and USD/CAD particularly for 5% VaR, suggesting that the former could serve as a good hedge against oil market instability.

Following this introduction, we offer further motivation for the predictability analysis of oil and exchange rate tail risks in Section 2, Section 3 describes the methodology and data, while Section 4 contains the results. Finally, the conclusion of the paper with some implications for investors is rendered in Section 5.

2. Further motivation for the predictability analysis of oil and exchange rate tail risks

Beyond establishing the relationships that exist between economic variables, predictability analysis makes correct prediction or forecast about economic fundamentals possible. That is, it ascertains how the nexus so established will behave if subjected to some other different data and/or within the relevant range of conditions (Ehrenberg & Bound, 1993).

Meanwhile, the usage transcends the field of business and finance (see for example, Sang & Li, 2002; Mehta et al. 2011). In contrast to the random walk hypothesis which posits that returns should be completely unpredictable, plethora of studies have uncovered cross-sectional relations between predetermined variables and future returns (Qi, 1999; Rapach et al., 2010, 2013; Salisu and Mobolaji, 2013; Salisu et al. 2021; Oloko et al., 2021; Iyke et al., 2022), as this offers various economic players (especially investors) to make some informed market decisions. However, there is a dearth of studies that relate the role of the extreme risks in the predictability analysis, thus, rather than using the actual series, this study uses the oil tail risk to predict the exchange rates tail risk in order to capture more inherent realities in the markets.

Economic theory as earlier mentioned, has explained the links between oil and exchange rate markets, especially for net-importing economies which rely heavily on the product as a source of energy for production purpose (see also Jain & Ghosh, 2013). In essence, shocks to oil price usually impact firms' domestic assets through exchange rate dynamics (Mahapatra & Bhaduri, 2019). Similarly, studies have shown that global crises usually trigger the positive co-movement between markets and exchange rate volatility, which usually influence investors' risk management strategies (see for example, Dua & Tuteja, 2016). Therefore, utilizing the information contained in the tail risk of oil for exchange rate tail risk tends to improve the forecastability of the return series (see for example, Ogbonna and Olubusoye, 2021; Salisu et al., 2021b, among others), and thus provide more robust information to profit maximizing investors when making investment decisions.

3. Methodology and Data

3.1 Theoretical arguments

The predictability of tail risk for US Dollar exchange rate is linked to tail risk of the crude oil market owing to the growing body of literature linking the movements in exchange rate to oil market (Amano and van Norden, 1998; Bénassy-Quéré et al., 2007; Ferraro et al., 2015; Pershin et al., 2016; Salisu et al., 2019a, 2020), given the fact that the crude oil market is priced in US Dollar and therefore any shock to the former (possibly due to slow down in the global economy and or supply constraints) is expected to affect the US Dollar market. The work of Salisu et al. (2020) offers different channels (i.e., trade and portfolio channels) through which oil price can influence exchange rate. In line with the trade channel, an increase in oil price leads to an increase in the price level of a large net oil importer like the US economy[10] given its large oil dependence in the tradable sector and therefore, the domestic currency depreciates (see Amano and van Norden, 1998; Bénassy-Quéré et al., 2007) while the reverse holds for a large net oil exporter. The portfolio channel (see Golub, 1983; Krugman, 1983; Turhan et al., 2014; Buetzer et al., 2016), suggest that an increase in oil price makes it possible for wealth to be transferred to oil-exporting countries, in terms of improvement in the current account balance, leading to appreciation in their currencies while currencies of oil-importers are expected to depreciate after an oil price increase. We depart from the literature in our analysis of the oil-exchange rate predictability as we focus essentially on the tail risks associated with the two markets rather than forecasting their return series. From the investment perspective, such outcomes help investors make informed decisions when confronted with alternative investment options in the presence of risks and the relevance becomes stronger when such decisions can be influenced by what happens in another market. Thus, we use the oil tail risk which enables us to capture the crude oil market risk to predict US Dollar tail risk. Summarily, the associated risks, corresponding to the oil and exchange rate markets, are first generated and thereafter used to examine the inherent nexus between oil and exchange rate markets.

3.2 Modelling Tail risks

Given the foregoing, we begin our analysis by constructing models required to generate the best fit tail risk using the conditional autoregressive value at risk (CAViaR) of the Engle & Manganelli (2004). Essentially, four models are considered in this regard - the Adaptive, Symmetric absolute value, Asymmetric slope and Indirect GARCH models and we follow the procedure of Engle & Manganelli (2004)[11] to estimate the models and consequently determine the "best" among them. One of the attractions to the CAViaR framework lies in its ability to utilize the asymptotic form of the tail, rather than modelling the whole distribution and therefore the risk measure seems to mirror the extreme movements in the return series typical of most financial and

[10] We do acknowledge that the US economy has recently (since 2019) become one of the top oil exporters, however, given the long range data of several decades used in this study, where the country is classified as a net oil importer, the former classification is unlikely to have any significant influence as regards the direction of connection between oil and Dollar exchange rates.

[11] 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.

energy series. While the details of the CAViaR are available in Engle & Manganelli (2004) and related studies such as Ogbonna and Olubusoye, 2021 and Salisu et al. (2021a, 2021b, 2021c, 2021d), they are represented here for ease of comprehension of the estimation procedure of the tail risk. A generic CAViaR specification proposed by Engle & Manganelli (2004) is given as:

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

where $f_t(\beta)\equiv f_t\left(x_{t-1},\beta_\theta\right)$ 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 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 $l\left(x_{t-j}\right)$ is to link $f_t(\beta)$ to observable variables that belong to the information set. The four variants (that is, the Adaptive, Symmetric absolute value, Asymmetric slope and Indirect GARCH models) estimated are derived from the generic specification and are respectively specified as follows:[12]

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:

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

Indirect GARCH (1,1):

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

[12] The use of the CAVaiR models to measure tail risks is increasingly gaining momentum in the literature with recent studies applying these models to forecast oil tail risk (see Salisu et al., 2021a), analyze the connection between tail risks and stock returns of advanced economies (Salisu et al., 2021b) and Asian economies (Ogbonna and Olubusoye, 2021), oil tail risks in the predictability of tail risks of Canada and the U.S. (Salisu et al., 2021c) and geopolitical risk and oil tail risk (Salisu et al., 2021d).

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 $\beta_1\left[I\left(y_{t-1} \leq f_{t-1}(\beta_1)\right)-\theta\right]$ if $G \rightarrow \infty$ with $I(\cdot)$ representing the indicator function. Note that equations (2), (3) and (5) are symmetric while only equation (4) is asymmetric where the response to positive and negative returns is identical. Also, the adaptive model has a unit coefficient on the lagged VaR while the other three are mean reverting implying that the coefficient on the lagged VaR is not constrained to be 1. After estimating all the four variants, we compute the Dynamic Quantile (DQ) statistic, %Hits and Regression Quantile (RQ) statistic [13] to determine the model that best fits the data. We expect the %Hits to be 1% for 1% VaR and 5% for 5% VaR; the DQ test statistic is not expected to be significant while the parameters are expected to minimize the RQ loss function, so the smaller the RQ statistic, the better. Nonetheless, the DQ test takes prominence over other statistics while we consider both the %Hits and the RQ statistic to determine the model with the best fit in situations where more than one tail risk is statistically insignificant in terms of the DQ test. Note that the tail risks analysis is distinctly carried out for oil price and US exchange rate market. Hence, given the aforementioned criteria (%Hits and the RQ statistic) for ascertaining the model with the best fit, the optimal measures of risks (at 1% and 5% VaR) associated with the oil and exchange rate markets are generated.

3.3 Constructing a predictive model for exchange rate with Tail risks

Based on the foregoing discussions in Sections 3.1 and 3.2, we formulate a predictive model for the tail risk predictability of exchange rate base on oil tail risk relying on the trade channel as previously espoused. We follow the approach of the Westerlund and Narayan (2012, 2015) which accounts for other additional salient features of the predicator series such as endogeneity, persistence and conditional heteroscedasticity effects[14]. Accounting for the additional effects is found to improve return predictability (see Bannigidadmath and Narayan

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

[14] Studies involving oil price as a predictor of return predictability such as Narayan and Gupta (2015), Salisu et al. (2019a, 2019b, 2019c, 2020) as well as those involving other predictors of return predictability (see Bannigidadmath and Narayan 2016; Narayan and Bannigidadmath, 2015; Phan et al., 2015; Devpura et al., 2018) have confirmed the presence of these effects particularly for high frequencies including the monthly frequency used in this study. Our preliminary tests of these effects whose results are available upon request also attest to this claim.

2016; Narayan and Bannigidadmath, 2015; Narayan and Gupta, 2015; Phan et al., 2015; Devpura et al., 2018; Salisu et al., 2019a, 2019b, 2019c, 2020). The predictive model is specified as:

$$tr_t^{exr} = \alpha + \sum_{i=1}^{5} \beta_i tr_{t-j}^{oil} + \gamma\left(tr_t^{oil} - \rho tr_{t-1}^{oil}\right) + \varepsilon_t \tag{6}$$

where tr_t^{exr} is the tail risk of exchange rate at period t obtained for each of the USD currency pairs (i.e. USD/GBP, USD/CAD and USD/JPY); α is the intercept; tr_t^{oil} is the oil tail risk while ε_t is the zero mean idiosyncratic error term. Note that the tail risks for both exchange rate and oil price returns are those obtained as the "best" tail risks using the Dynamic Quantile (DQ) statistic, %Hits and Regression Quantile (RQ) statistic, as previously noted. The underlying predictability test has the null hypothesis - $\sum_{i=1}^{5} \beta_i = 0$ where five lags are included in the predictability analysis to capture more dynamics since daily frequency is used. We employ the Wald joint test to evaluate the null hypothesis and a rejection of the null hypothesis implies the predictability of oil tail risk for Dollar tail risk, while a non-rejection suggests no connection between the two tail risks. An additional term - $\gamma\left(tr_t^{oil} - \rho tr_{t-1}^{oil}\right)$ is included in the predictive model to resolve any inherent endogeneity bias (that may have arisen from model misspecification and/or omitted variables, which may also include structural break dummy) as well as persistence effect. The choice of high (daily) frequency (with over 8000 observations) 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 of the residual obtained from the GARCH(1,1) model and estimating the resulting equation with the Ordinary Least Squares to obtain the Feasible Quasi Generalized Least Squares estimates.

The final step of the analysis involves the out-of-sample forecast evaluation of equation (6) relative to a benchmark (random walk) model that ignores the role of oil tail risk in the predictability of the tail risk for exchange rate returns. 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.[15] We adopt the expanded

[15] 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

(recursive) window approach which accommodates some inherent time-variation in the estimation process to generate the forecast estimates.

3.4 Data and some descriptive analyses

This study utilizes daily data covering US Dollar/British pound sterling (abbreviated as USD/GBP)[16] and crude oil prices (both Brent and the West Texas Intermediate crude oil prices) over the period of May 21, 1987 through March 11, 2021 where the start date is conditioned on the availability of daily frequency for the oil prices. Our source of data is the Economic database of the Federal Reserve Bank of St. Louis (see https://fred.stlouisfed.org/). The US Dollar has remained the world currency and as such, the most traded currency in the world (see Seetharaman et al., 2017) and therefore its connection with oil price, which is a global factor capable of influencing the level of real economic activity in a large open economy like the U.S., is worth investigating. We offer some preliminary statistics here before discussing the main findings of the study. For this purpose, we use the log returns computed as the first-difference of the natural logarithm of the series multiplied by 100 to circumvent unit root problem.

The descriptive statistics are presented in Table 1 and we find that, on average, the oil market offers a higher return than the USD/GBP foreign exchange market while Brent crude has a higher return than the WTI crude. In line with the risk-return trade-off (where higher risks are associated with greater probability of higher returns and lower risks with a greater probability of smaller returns), we find that the oil market (which offers a higher return, on the average) is more risky than the USD/GBP foreign exchange market judging by both the Standard deviation and Coefficient of Variation (CV) statistics. Looking at the distribution of the return series, evidence favors negative skewness and leptokurtosis for all the returns series suggesting the presence of heavy tails and by extension non-normality of the series which is further validated with the Jarque-Bera test. Therefore, modelling with the tail risks of the predicted and predictor series is justified empirically in addition to the investment implications of pursuing this empirical exercise.

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and Gupta, 2015) and the outcome is observed to be insensitive to the choice of data split (see Narayan and Gupta, 2015; Salisu et al., 2019b, 2019c).

[16] Aside the fact that the interest is in US Dollar exchange rate where the US Dollar is expressed against another currency, the USD/GBP is in fact the natural way the exchange rate is traded in the foreign exchange market. Thus, analyses obtained from using this Dollar exchange rate would have investment implications beyond the predictability results.

Table 1: Summary statistics for the log returns of oil prices and the three USD currency pairs considered [21-05-1987 - 11-03-2021]

	Mean	Std. Dev.	CV	Skewness	Kurtosis	J-B test	Nobs
USD/GBP	-0.0021	0.6059	-288.092	-0.4768	10.262	19718.63***	8821
USD/JPY	0.0029	0.6656	229.517	0.3131	9.108	13858.42***	8821
USD/CAD	0.0009	0.4791	523.333	0.1471	10.806	22427.24***	8821
Brent	0.0149	2.5332	170.024	-1.8285	72.577	1784174***	8821
WTI	0.0093	4.3975	473.160	-38.9177	2599.141	2.48E+09***	8821

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

4. Results and Discussion

4.1 Main Findings

We utilize the best tail risks in the estimation of the predictive model in (6). We follow the procedure of Engle and Manganelli (2004) to determine the best tail risks and the return series of the relevant variables are used since investors rely more on returns than prices when making investment decisions coupled with the need to circumvent any unit root problem. We estimate the four CAViaR specifications in (2) to (4) for both 1% and 5% VaRs and choose the 'best" tail risk for each return series based on certain criteria. Essentially, for the "best" tail risk variant, we consider three criteria for both the in-sample and out-of-sample forecasts: (i) the %Hits; (ii) the Dynamic Quantile (DQ) test; and (iii) the Regression Quantile (RQ) statistic. We expect the %Hits to be 1% for 1% VaR and 5% for 5% VaR; the DQ test statistic is not expected to be significant while the parameters are expected to minimize the RQ loss function, so the smaller the RQ statistic, the better. Nonetheless, the DQ test takes prominence over other statistics while we consider both the %Hits and the RQ statistic to determine the model with the best fit in situations where more than one tail risk is statistically insignificant in terms of the DQ test. The estimates of the CAViaR specifications including the mentioned diagnostics are reported in Tables 2, 3, 4, 5 and 6 for Brent crude oil, WTI crude oil, US Dollar/British pound sterling, Dollar/Canadian Dollar and Dollar/Japanese Yen exchange rate returns, respectively. One striking evidence from the estimates is that the choice of best tail risk is sensitive to the choice of VaR. For instance, we find that the Indirect GARCH produces the best tail risk for Brent crude oil returns with 1% VaR while the Asymmetric model is favoured with 5% VaR. Similarly for WTI crude oil, the Indirect GARCH is the best candidate with 1% VaR while the Symmetric Absolute Value best fits the series with 5% VaR. The predicted risks from the corresponding ascertained optimal CAViaR models for the oil and exchange rate markets, under the 1% and 5% VaRs are used to proxy the risk associated with the markets. The consideration of 1% and 5% VaRs is to provide a basis for conducting robustness checks, in a bid to ascertain that the predictability results are not sensitive to the % VaRs used. Hence, the risks associated with oil and exchange rate markets are denoted as oil tail risk (the predictor) and USD currency pairs' tail risks (the predicted series).

Table 2: CAViaR analysis for Brent crude oil returns, 5/21/1987 - 3/11/2021

	SAV		ASY		GARCH		ADAPTIVE	
Brent_USD	1% VaR	5% VaR	1% VaR	5% VaR	1% VaR	5% VaR	1% VaR	5% VaR
Beta1	0.2390	0.0995	0.0533	**0.0557**	**0.4800**	0.1970	1.1800	0.4130
Standard errors	0.0898	0.0198	0.0676	**0.0258**	**0.1270**	0.0914	0.0185	0.0414
P values	0.0039	0.0000	0.2150	**0.0154**	**0.0001**	0.0156	0.0000	0.0000
Beta2	0.8820	0.9350	0.8980	**0.9340**	**0.8620**	0.9140		
Standard errors	0.0217	0.0164	0.0639	**0.0221**	**0.0045**	0.0097		
P values	0.0000	0.0000	0.0000	**0.0000**	**0.0000**	0.0000		
Beta3	0.3800	0.1110	0.3210	**0.0796**	**0.9570**	0.1950		
Standard errors	0.0975	0.0263	0.2340	**0.0359**	**0.2850**	0.1670		
P values	0.0000	0.0000	0.0848	**0.0133**	**0.0004**	0.1210		
Beta4			0.3330	**0.1360**				
Standard errors			0.2510	**0.0377**				
P values			0.0924	**0.0002**				
RQ	574.00	1890.00	574.00	**1880.00**	**567.00**	1890.00	638.00	1930.00
Hits in-sample (%)	1.0100	4.9900	0.9970	**4.9900**	**0.9970**	5.0500	0.9970	4.8800
Hits out-of-sample (%)	1.6000	5.7100	1.6000	**5.8100**	**1.3000**	5.6100	1.7000	5.3100
DQ in-sample (P-values)	0.1430	0.0451	0.1330	**0.1490**	**0.4900**	0.1450	0.0058	0.6010
DQ out-of-sample (P-values)	0.0859	0.0115	0.0970	**0.0135**	**0.2570**	0.6680	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 the in-sample. For the "best" tail risk variant, we consider three criteria: (i) %Hits; (ii) DQ test; and (iii) RQ statistic. We expect the %Hits to be 1% for 1% VaR and 5% for 5% VaR; the DQ test statistic is not expected to be significant while the parameters are expected to minimize the RQ loss function, so the smaller the RQ statistic, the better. Nonetheless, the DQ test takes prominence over other statistics while we consider both the %Hits and the RQ statistic to determine the model with the best fit in situations where more than one tail risk is statistically insignificant in terms of the DQ test.

Table 3: CAViaR analysis for WTI crude oil returns, 5/21/1987 - 3/11/2021

	SAV		ASY		GARCH		ADAPTIVE	
	1% VaR	5% VaR	1% VaR	5% VaR	1% VaR	5% VaR	1% VaR	5% VaR
Beta1	0.1820	**0.1440**	0.0895	0.0792	**0.6840**	0.2990	1.1700	0.7370
Standard errors	0.0727	**0.0259**	0.0921	0.0207	**0.2570**	0.1240	0.0243	0.0312
P values	0.0062	**0.0000**	0.1660	0.0001	**0.0039**	0.0078	0.0000	0.0000
Beta2	0.9130	**0.9050**	0.9110	0.9020	**0.9030**	0.8980		
Standard errors	0.0181	**0.0160**	0.0256	0.0128	**0.0114**	0.0143		
P values	0.0000	**0.0000**	0.0000	0.0000	**0.0000**	0.0000		
Beta3	0.2650	**0.1580**	0.2990	0.1680	**0.5030**	0.2020		
Standard errors	0.0213	**0.0265**	0.0352	0.0315	**0.0886**	0.0640		
P values	0.0000	**0.0000**	0.0000	0.0000	**0.0000**	0.0008		
Beta4			0.2090	0.1520				
Standard errors			0.0435	0.0236				
P values			0.0000	0.0000				
RQ	597.00	**1980.00**	599.00	1980.00	**600.00**	1980.00	685.00	2050.00
Hits in-sample (%)	1.0100	**5.0100**	0.9840	5.0000	**1.0100**	5.0100	1.0100	4.9600
Hits out-of-sample (%)	1.5000	**6.1100**	1.5000	6.3100	**1.3000**	5.5100	1.6000	5.0100
DQ in-sample (P-values)	0.3370	**0.4150**	0.3050	0.1970	**0.6020**	0.0951	0.0619	0.0288
DQ out-of-sample (P-values)	0.0000	**0.1080**	0.0001	0.0176	**0.2880**	0.1020	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 the in-sample. For the "best" tail risk variant, we consider three criteria: (i) %Hits; (ii) DQ test; and (iii) RQ statistic. We expect the %Hits to be 1% for 1% VaR and 5% for 5% VaR; the DQ test statistic is not expected to be significant while the parameters are expected to minimize the RQ loss function, so the smaller the RQ statistic, the better. Nonetheless, the DQ test takes prominence over other statistics while we consider both the %Hits and the RQ statistic to determine the model with the best fit in situations where more than one tail risk is statistically insignificant in terms of the DQ test.

Table 4: CAViaR analysis for USD/GBP returns, 5/21/1987 - 3/11/2021

USD_GBP	SAV 1% VaR	SAV 5% VaR	ASY 1% VaR	ASY 5% VaR	GARCH 1% VaR	GARCH 5% VaR	ADAPTIVE 1% VaR	ADAPTIVE 5% VaR
Beta1	0.0916	**0.0504**	**0.0425**	0.0144	0.0648	0.0154	0.4210	0.1530
Standard errors	0.0353	**0.0036**	**0.0119**	0.0082	0.0301	0.0036	0.0638	0.0128
P values	0.0047	**0.0000**	**0.0002**	0.0405	0.0156	0.0000	0.0000	0.0000
Beta2	0.9200	**0.9290**	**0.9130**	0.9300	0.8980	0.9190		
Standard errors	0.0367	**0.0055**	**0.0158**	0.0164	0.0174	0.0053		
P values	0.0000	**0.0000**	**0.0000**	0.0000	0.0000	0.0000		
Beta3	0.2850	**0.1840**	**0.1840**	0.1020	0.5290	0.1840		
Standard errors	0.0620	**0.0113**	**0.0385**	0.0204	0.3220	0.0392		
P values	0.0000	**0.0000**	**0.0000**	0.0000	0.0502	0.0000		
Beta4			**0.2260**	0.1390				
Standard errors			**0.0347**	0.0358				
P values			**0.0000**	0.0001				
RQ	151.00	**517.00**	**150.00**	517.00	148.00	515.00	161.00	529.00
Hits in-sample (%)	0.9970	**5.0100**	**1.0200**	5.0100	1.0100	5.0000	0.8180	4.3000
Hits out-of-sample (%)	1.5000	**4.9000**	**1.1000**	4.2000	1.1000	4.4000	0.8010	4.3000
DQ in-sample (P-values)	0.3150	**0.9030**	**0.8700**	0.3780	0.1760	0.3850	0.0054	0.0121
DQ out-of-sample (P-values)	0.1310	**0.8690**	**0.5710**	0.7320	0.8390	0.7780	0.0292	0.1780

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 the in-sample. For the "best" tail risk variant, we consider three criteria: (i) %Hits; (ii) DQ test; and (iii) RQ statistic. We expect the %Hits to be 1% for 1% VaR and 5% for 5% VaR; the DQ test statistic is not expected to be significant while the parameters are expected to minimize the RQ loss function, so the smaller the RQ statistic, the better. Nonetheless, the DQ test takes prominence over other statistics while we consider both the %Hits and the RQ statistic to determine the model with the best fit in situations where more than one tail risk is statistically insignificant in terms of the DQ test.

Table 5: CAViaR analysis for USD/CAD returns, 5/21/1987 - 3/11/2021

	SAV		ASY		GARCH		ADAPTIVE	
	1% VaR	5% VaR	1% VaR	5% VaR	1% VaR	5% VaR	1% VaR	5% VaR
Beta1	**0.0548**	0.0181	0.0155	0.0042	0.0153	**0.0025**	0.3460	0.1870
Standard errors	**0.0049**	0.0017	0.0039	0.0010	0.0037	**0.0010**	0.0536	0.0190
P values	**0.0000**	0.0000	0.0000	0.0000	0.0000	**0.0077**	0.0000	0.0000
Beta2	**0.9390**	0.9670	0.9380	0.9510	0.9340	**0.9480**		
Standard errors	**0.0059**	0.0037	0.0102	0.0035	0.0034	**0.0028**		
P values	**0.0000**	0.0000	0.0000	0.0000	0.0000	**0.0000**		
Beta3	**0.2740**	0.1140	0.1290	0.0909	0.3300	**0.1290**		
Standard errors	**0.0243**	0.0052	0.0326	0.0114	0.5830	**0.1650**		
P values	**0.0000**	0.0000	0.0000	0.0000	0.2860	**0.2160**		
Beta4			0.1840	0.0930				
Standard errors			0.0541	0.0029				
P values			0.0003	0.0000				
RQ	**111.0000**	388.0000	108.0000	376.0000	107.0000	**375.0000**	115.0000	386.0000
Hits in-sample (%)	**0.9970**	5.0000	0.9970	4.9900	0.9970	**5.0400**	0.7160	3.5800
Hits out-of-sample (%)	**0.9010**	6.1100	1.2000	5.0100	1.2000	**4.9000**	0.6010	3.5000
DQ in-sample (P-values)	**0.3900**	0.0022	0.0785	0.0090	0.4630	**0.2070**	0.7450	0.0158
DQ out-of-sample (P-values)	**0.1070**	0.0003	0.2520	0.0005	0.0212	**0.2770**	0.0061	0.1710

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 the in-sample. For the "best" tail risk variant, we consider three criteria: (i) %Hits; (ii) DQ test; and (iii) RQ statistic. We expect the %Hits to be 1% for 1% VaR and 5% for 5% VaR; the DQ test statistic is not expected to be significant while the parameters are expected to minimize the RQ loss function, so the smaller the RQ statistic, the better. Nonetheless, the DQ test takes prominence over other statistics while we consider both the %Hits and the RQ statistic to determine the model with the best fit in situations where more than one tail risk is statistically insignificant in terms of the DQ test.

Table 6: CAViaR analysis for USD/JPY returns, 5/21/1987 - 3/11/2021

	SAV		ASY		GARCH		ADAPTIVE	
	1% VaR	5% VaR	1% VaR	5% VaR	1% VaR	5% VaR	1% VaR	5% VaR
Beta1	**0.0747**	0.0268	0.0507	0.0286	0.0571	**0.0175**	0.4290	0.1110
Standard errors	**0.0129**	0.0030	0.0183	0.0094	0.0202	**0.0069**	0.0332	0.0220
P values	**0.0000**	0.0000	0.0029	0.0011	0.0023	**0.0060**	0.0000	0.0000
Beta2	**0.9380**	0.9630	0.9160	0.9240	0.9280	**0.9410**		
Standard errors	**0.0120**	0.0051	0.0140	0.0132	0.0093	**0.0076**		
P values	**0.0000**	0.0000	0.0000	0.0000	0.0000	**0.0000**		
Beta3	**0.2130**	0.0813	0.2580	0.1360	0.3180	**0.1030**		
Standard errors	**0.0404**	0.0053	0.0388	0.0153	0.9510	**0.0936**		
P values	**0.0000**	0.0000	0.0000	0.0000	0.3690	**0.1350**		
Beta4			0.1040	0.0701				
Standard errors			0.0272	0.0196				
P values			0.0001	0.0002				
RQ	**163.0000**	563.0000	162.0000	562.0000	163.0000	**561.0000**	179.0000	577.0000
Hits in-sample (%)	**0.9840**	5.0000	0.9840	4.9900	0.9970	**4.9900**	0.8950	4.3500
Hits out-of-sample (%)	**0.3000**	2.6000	0.2000	1.9000	0.3000	**2.4000**	0.6010	3.1000
DQ in-sample (P-values)	**0.8320**	0.3250	0.4000	0.4360	0.1380	**0.4770**	0.9070	0.8410
DQ out-of-sample (P-values)	**0.5510**	0.0019	0.3620	0.0014	0.5510	**0.0032**	0.0055	0.0176

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 the in-sample. For the "best" tail risk variant, we consider three criteria: (i) %Hits; (ii) DQ test; and (iii) RQ statistic. We expect the %Hits to be 1% for 1% VaR and 5% for 5% VaR; the DQ test statistic is not expected to be significant while the parameters are expected to minimize the RQ loss function, so the smaller the RQ statistic, the better. Nonetheless, the DQ test takes prominence over other statistics while we consider both the %Hits and the RQ statistic to determine the model with the best fit in situations where more than one tail risk is statistically insignificant in terms of the DQ test.

Having obtained the best tail risks for both the predicted and the predictor series, we proceed to estimate the predictive model in (6) to determine the predictability of oil tail risk for all the three USD currency pairs' tail risks and the results for both the full sample and the COVID sample period are presented in Table 7. At both 1% and 5% VaRs, we find that the oil tail risk is statistically significant and positively related with the tail risks of USD/GBP and USD/CAD exchange rates. The estimates under the full sample and COVID period do not seem to differ markedly. This reveals that rising oil market risk is likely to cause the risks associated with USD/GBP and USD/CAD exchange rates' markets to rise. This validates the existence of possible risk spillovers from the oil market to the foreign exchange market (see also, Salisu and Mobolaji, 2013) and more importantly, this evidence speaks to the long-standing connection between the US and these economies and therefore the positive risk spillovers between the two economies is justified. On the contrary, at 5% VaRs, our results indicate that oil tail risk is statistically significant and negatively related with the tail risk of USD/JPY exchange rate. This implies that higher risk in the oil market may lead to reduced risks in the USD/JPY exchange rate market. This outcome suggests that USD/JPY is resilient to possible risk spillovers from the oil market and could serve as a good hedge during instabilities associated with oil market (see also Liao and Zhang, 2021). These mixed findings for the considered US Dollar exchange rates are not unexpected. Essentially, movements in these exchange rates are more correlated in nations with huge oil reserves such as the United Kingdom and Canada; and less correlated in nations with no significant crude oil reserves like Japan. In other words, economies such as the United Kingdom and Canada with excess crude reserves would have their currencies depreciated when the risk associated with oil market is high while USD/JPY appreciates. Empirical results on the effects of positive shock to oil price on exchange rates of oil-exporting and oil-importing countries abound (see Salisu et al., 2020 for example). Similar evidence regarding the tail risk dependence between crude oil and foreign exchange markets is reported for MENA and some developed countries (see for example, Mensi et al., 2017). Furthermore, there is evidence of significant risk spillovers from crude oil market to exchange rate market of the U.S (see Ji, Liu & Fan 2019), thus explaining the reason for the depreciation of USD/CAD currency pair since these two countries have a history of long standing economic ties (see Salisu et al., 2021c). Moreover, our results confirm the safe-haven status which USD/JPY has attained since early 2000s. This has been attributed to the large external financial imbalances of Japan (see Liao and Zhang, 2021). Furthermore, yen has been quite stable in the foreign exchange markets over the years. Particularly, USD/JPY traded in a range of 7.6% in 2019 – its tightest since 1980. This range has been less than 10% every year since the last three years.[17] All these have a way of boosting investors' confidence in yen during periods of high oil price risk.

[17] See https://disruptionbanking.com/2021/02/10/the-puzzle-of-the-japanese-yens-safe-haven-status/

Table 7: Predictability results for exchange rates Tail risk

	Full Sample				COVID Period			
	1 % tail risk		5% tail risk		1 % tail risk		5% tail risk	
	BRENT	**WTI**	**BRENT**	**WTI**	**BRENT**	**WTI**	**BRENT**	**WTI**
				USD/GBP				
Oil tail risk [$\sum_{i=1}^{5} \beta_i tr_{t-j}^{oil}$]	0.0516*** (0.0017)	0.0647*** (0.0015)	0.1486*** (0.0024)	0.1247*** (0.0020)	0.0850*** (0.0017)	0.0637*** (0.0014)	0.1486*** (0.0024)	0.1257*** (0.0020)
				USD/CAN				
Oil tail risk [$\sum_{i=1}^{5} \beta_i tr_{t-j}^{oil}$]	0.1502*** (0.0027)	0.0253*** (0.0015)	0.1615*** (0.0026)	0.1871*** (0.0021)	0.1512*** (0.0027)	0.0253*** (0.0015)	0.1615*** (0.0026)	0.1875*** (0.0021)
				USD/JPY				
Oil tail risk [$\sum_{i=1}^{5} \beta_i tr_{t-j}^{oil}$]	0.0007 (0.0024)	-0.0027 (0.0034)	-0.0094*** (0.0024)	-0.0159*** (0.0006)	0.0007 (0.0024)	-0.0027 (0.0034)	-0.0094*** (0.0024)	0.0414*** (0.0039)
Start date	20/05/19 87	20/05/198 7	20/05/198 7	20/05/198 7	01/01/202 0	01/01/202 0	01/01/202 0	01/01/202 0
End date	11/3/202 1	11/3/2021	11/3/2021	11/3/2021	11/3/2021	11/3/2021	11/3/2021	11/3/2021
Nobs	8821	8821	8821	8821	311	311	311	311

Note: BRENT and WTI represent the returns to oil prices, and are computed as $100 * \Delta \log(p_t)$, where p_t is the price. ***, ** and * represent 1%, 5% and 10% significant levels respectively. Values in parentheses represent standard errors. Nobs means number of observations. $\sum_{i=1}^{5} \beta_i tr_{t-j}^{oil}$ denotes the use of Wald joint test to evaluate the null hypothesis and a rejection of the null hypothesis implies the predictability of oil tail risk for Dollar tail risk, while a non-rejection suggests no connection between the two tail risks.

Our findings will come in handy for policymakers who are on the lookout for the appropriate currency to quote in their foreign reserves to avoid possible risk associated with USD due to crude oil risk, since the risk spillover is capable of affecting foreign exchange gain as well as the capital inflows. To the investors and portfolio managers, quoting their stock of foreign currency in yen will help them in hedging against risk associated with crude oil and by extension, USD.

Further analysis to see if the predictive value of the oil tail risk can be exploited to improve the forecasts of all the tail risks of the three USD currency pairs, shows that including the former in the predictive model of the latter is not only capable of improving in-sample forecast but also the out-of-sample forecast outcomes (see Tables 8, 9 and 10). There seems to be a slight difference between the stance under the full sample and the COVID sample period. However, on a general note, the conclusion of our predictive model performing better than the random walk model is upheld. This conclusion is insensitive to the choice of oil proxy, chosen sample periods and VaR, save WTI at 1% tail risk for USD/JPY, and therefore, strengthens our earlier predictability results which show significant contributions of the oil tail risk to the exchange rate tail risk. Overall, investors seeking to maximize returns in the US Dollar foreign exchange market may need to take cognizance of the dynamics in the oil market as well as the associated risks in order to take well informed investment decisions.

Table 8: In-Sample and Out-of-Sample Forecast Evaluation [USD/GBP] Results

Horizon	Full Sample				COVID Period			
	1 % tail risk		5 % tail risk		1 % tail risk		5 % tail risk	
	BRENT	WTI	BRENT	WTI	BRENT	WTI	BRENT	WTI
	Clark & West							
In-Sample	0.0468*** [4.0722]	0.0542*** [4.6978]	0.0541*** [5.0858]	0.0604*** [5.5762]	0.2366*** [3.4946]	0.3579*** [3.4587]	0.1847*** [2.8046]	0.4001*** [4.9723]
Out-of-Sample								
h=15	0.0452*** [3.9378]	0.0526*** [4.5671]	0.0533*** [5.0180]	0.0596*** [5.5107]	0.2370*** [3.7098]	0.3534*** [3.6183]	0.1846*** [2.9668]	0.3817*** [5.0172]
h=30	0.0437*** [3.8104]	0.0511*** [4.4448]	0.0525*** [4.9539]	0.0589*** [5.4541]	0.2212*** [3.6479]	0.3317*** [3.5804]	0.1717*** [2.9021]	0.3604*** [4.9906]
h=60	0.0420*** [3.6805]	0.0495*** [4.3205]	0.0510*** [4.8357]	0.0575*** [5.3470]	0.1544*** [2.7575]	0.2459*** [2.8928]	0.1252** [2.3174]	0.3135*** [4.7676]
	RMSE							
In-Sample	0.8995	0.8527	0.8643	0.8115	0.9759	1.6006	1.1330	1.0218
Out-of-Sample								
h=15	0.9002	0.8534	0.8643	0.8116	0.9509	1.5573	1.1173	0.9949
h=30	0.9008	0.8541	0.8642	0.8115	0.9361	1.5227	1.1085	0.9720
h=60	0.9005	0.8539	0.8638	0.8112	0.9400	1.4849	1.1039	0.9395

Note: C-W is the Clark and West test while RMSE is Root Mean Square Error. The RMSE is the version of Clark and West (2007) which adjusts the difference in mean squared prediction errors to account for the additional predictors in the model. ***, ** and * represent 1%, 5% and 10% significance levels respectively. Values reported in square brackets are the t-statistics. For the Clark & West test, the null hypothesis of a zero coefficient is rejected if this 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 a one sided 0.01 test) (see Clark & West, 2007).

Table 9: In-Sample and Out-of-Sample Forecast Evaluation [USD/CAD] Results

Horizon	Full Sample				COVID Period			
	1 % tail risk		5 % tail risk		1 % tail risk		5 % tail risk	
	BRENT	WTI	BRENT	WTI	BRENT	WTI	BRENT	WTI
				Clark & West				
In-Sample	0.2620*** [7.0696]	0.2641*** [7.3019]	0.0806*** [7.2983]	0.0939*** [8.5171]	0.1945*** [4.7471]	0.1042** [2.0898]	0.0807*** [10.0210]	0.1039*** [4.4666]
Out-of-Sample								
h=15	0.2609*** [7.0560]	0.2629*** [7.2850]	0.0802*** [7.2782]	0.0935*** [8.4978]	0.1725*** [4.4182]	0.0748 [1.5704]	0.0788*** [10.3391]	0.0965*** [4.3814]
h=30	0.2600*** [7.0475]	0.2618*** [7.2706]	0.0798*** [7.2604]	0.0931*** [8.4813]	0.1513*** [4.0524]	0.0463 [1.0117]	0.0766*** [10.5881]	0.0902*** [4.3152]
h=60	0.2586*** [7.0415]	0.2601*** [7.2572]	0.0793*** [7.2410]	0.0925*** [8.4633]	0.1193*** [3.4852]	0.0034 [0.0817]	0.0743*** [11.3242]	0.0787*** [4.1415]
				RMSE				
In-Sample	1.3247	1.3082	0.7112	0.6235	0.6032	0.9404	0.1774	0.3824
Out-of-Sample								
h=15	1.3238	1.3074	0.7107	0.6232	0.6051	0.9479	0.1729	0.3757
h=30	1.3225	1.3064	0.7102	0.6228	0.6090	0.9565	0.1694	0.3686
h=60	1.3198	1.3041	0.7090	0.6217	0.6106	0.9670	0.1627	0.3589

Note: Same as Table 8.

Table 10: In-Sample and Out-of-Sample Forecast Evaluation [USD/JPY] Results

Horizon	Full Sample				COVID Period			
	1 % tail risk		5 % tail risk		1 % tail risk		5 % tail risk	
	BRENT	WTI	BRENT	WTI	BRENT	WTI	BRENT	WTI
				Clark & West				
In-Sample	0.0902*** [4.6857]	0.0109 [0.6068]	0.0341*** [5.2050]	0.0155*** [2.5104]	0.1549*** [2.7452]	0.2529*** [3.6934]	0.0788*** [5.0412]	0.0840*** [4.3902]
Out-of-Sample								
h=15	0.0883*** [4.5962]	0.0087 [0.4843]	0.0334*** [5.1114]	0.0147*** [2.3909]	0.1234** [2.2927]	0.2197*** [3.3717]	0.0715*** [4.8095]	0.0757*** [4.1669]
h=30	0.0862*** [4.4942]	0.0058 [0.3259]	0.0327*** [5.0112]	0.0139*** [2.2516]	0.0906* [1.7560]	0.1862*** [2.9921]	0.0642*** [4.5229]	0.0676*** [3.8989]
h=60	0.0857*** [4.4876]	0.0058 [0.3280]	0.0323*** [4.9763]	0.0136*** [2.2131]	0.0311 [0.6513]	0.1251** [2.1866]	0.0517*** [4.5229]	0.0527*** [3.3225]
				RMSE				
In-Sample	1.5345	1.6704	0.8674	0.9108	1.0263	1.1857	0.3928	0.4765
Out-of-Sample								
h=15	1.5345	1.6710	0.8674	0.9111	1.0310	1.1742	0.3892	0.4708
h=30	1.5344	1.6718	0.8674	0.9114	1.0380	1.1659	0.3878	0.4671
h=60	1.5329	1.6717	0.8666	0.9112	1.0515	1.1543	0.3856	0.4626

Note: Same as Table 8

4.2 Additional Analyses

We further consider alternative benchmark models involving autoregressive models with lags 1 (AR(1)) and 2 (AR(2)) and by implication we use the (modified version) of the Diebold and Mariano (1995) [DM] test proposed by Harvey, Leybourne and Newbold (1997) rather than the Clark and West (2007) used in the previous section. The former approach is suitable for the forecast evaluation of non-nested models which is the case with the AR models and the proposed predictive models unlike in the latter case where the competing models are expected to be nested which is the case in Section 4.1. We define the modified DM test as:

$$DM^* = \left(\sqrt{\frac{T+1-2h+T^{-1}h\left(h-1\right)}{T}}\right)DM \tag{7}$$

where h is the forecast horizon; the originally developed Diebold and Mariano statistics is defined by $DM = \bar{d}\Big/\sqrt{V\left(d\right)\big/T} \sim N\left(0,1\right)$; the average and the unconditional variance of the loss differential between the two competing models are respectively defined as $\bar{d} = \frac{1}{T}\sum_{t=1}^{T} d_t$ and $V\left(d_t\right)$; the loss differential is given as $d_t \equiv l\left(\varepsilon_{tr}\right) - l\left(\varepsilon_{ar}\right)$, where $l\left(\varepsilon_{tr}\right)$ and $l\left(\varepsilon_{ar}\right)$ are the loss functions of the forecast error of the oil tail risk-based model and the autoregressive benchmark models. We test the null hypothesis $H_0 : E(d_t) = 0$ (forecast errors from both models do not differ markedly) against the alternative $\left(H_1 : E(d_t) < 0\right)$ that asserts that our oil tail risk-based distributed lag model to be more accurate than the benchmark (AR(1) and AR(2)-based) models. We evaluate the model adequacy both for the in-sample period as well as the out-of-sample periods (15-, 30, and 60-day ahead), under the full sample and the COVID periods.

In addition, we also employ the Model Confidence Sets (MCS) test for forecasting models developed by Hansen et al. (2011). It comprises a sequence of tests that are used to construct a set of "superior" models; under a null hypothesis of equal predictive ability (EPA) of the competing models at specified confidence level. In contrast with the Diebold and Mariano, a pairwise comparative tool, that is based on loss function; the MCS procedure compares more than two models by considering simultaneously all the competing models and sequentially eliminating the worst model until the EPA null hypothesis is accepted for the models in the set of superior models.

Suppose that M is a subset of some original models denoted by M^o, such that there are m models M; and given the loss differential, $d_{\rho\xi,\ell} = l_{\rho,\ell} - l_{\xi,\ell}$; $\rho,\xi = 1,\ldots,m$; $\ell = 1,\ldots,N$ between models ρ and ξ, the calculated loss of model ρ relative to any other model ξ at point ℓ defined by $d_{\rho.,\ell} = \frac{1}{m}\sum_{\xi\in M} d_{\rho\xi,\ell}$, $\rho = 1,\ldots,m$. Suppose also that the candidate models $c_{\rho\xi} = E\left(d_{\rho\xi}\right)$ and $c_{\rho.} = E\left(d_{\rho.}\right)$ are finite and time invariant, then the EPA hypothesis for a set of M candidate models can either be formulated as $H_{o,M} : c_{\rho\xi} = 0,\ \forall\ \rho,\xi = 1,\ldots,m$ or $H_{o,M} : c_{\rho.} = 0,\ \forall\ \rho = 1,\ldots,m$ against their mutually exclusive alternatives. The test statistic of the null hypothesis $\left(H_{o,M} : c_{\rho\xi} = 0\right)$ is defined as $T_{R,M} = \max_{\rho,\xi\in M}\left|t_{\rho\xi}\right|$ where $t_{\rho\xi} = \bar{d}_{\rho\xi}\Big/\sqrt{\hat{Var}\left(\bar{d}_{\rho\xi}\right)}$, $\bar{d}_{\rho\xi} = \frac{1}{m}\sum_{l=1}^{m}\bar{d}_{\rho\xi,\ell}$ is the relative sample loss between models ρ and ξ, and $\hat{Var}\left(\bar{d}_{\rho\xi}\right)$ is the bootstrapped estimates of $Var\left(\bar{d}_{\rho\xi}\right)$. The test statistic for the null hypothesis $\left(H_{o,M} : c_{\rho.} = 0\right)$ is defined by $T_{\max,M} = \max_{\rho\in M} t_{\rho.}$ where $t_{\rho.} = \bar{d}_{\rho.}\Big/\sqrt{\hat{Var}\left(\bar{d}_{\rho.}\right)}$, with $\bar{d}_{\rho.} = \frac{1}{m}\sum_{\xi\in M}^{m}\bar{d}_{\rho\xi}$ denoting the sample loss of model ρ in comparison with the average loss across all models; and $\hat{Var}\left(\bar{d}_{\rho.}\right)$ denoting the bootstrapped estimates of $Var\left(\bar{d}_{\rho.}\right)$. $T_{R,M}$ employs loss differential between the compared model pairs (ρ and ξ), while $T_{\max,M}$ uses the paired loss differentials aggregated over ξ. Under each hypothesis, the elimination rule for selecting the worst model is defined by test statistics $e_{R,M} = \arg\max_{\rho\in M}\left\{\sup_{\xi\in M}\left(\bar{d}_{\rho\xi}\Big/\sqrt{\hat{Var}\left(\bar{d}_{\rho\xi}\right)}\right)\right\}$ and $e_{\max,M} = \arg\max_{\rho\in M}\left(\bar{d}_{\rho.}\Big/\hat{Var}\left(\bar{d}_{\rho.}\right)\right)$.

The results of the Diebold and Mariano (1995) test and the model confidence sets are respectively presented on Tables 11 and 12. As a way of further robustness checks, we compare our distributed lag model with two autoregressive (lags 1 and 2) benchmark models, under the different exchange rate pairs (USD/GBP, USD/CAD and USD/JPY), oil proxies (Brent and WTI), tail risks (1% and 5%), sample periods (Full and COVID) as well as forecast horizons (In-sample, 15-, 30 and 60-day ahead out-of-sample). The Diebold and Mariano test results reveal overwhelming outperformance of our distributed lag model over the autoregressive benchmark models irrespective of the exchange pairs, tail risks, oil proxies and forecast horizons, under the full sample period (see the left pane on Table 11). However, the same cannot be said for the COVID period, as there were only significant outperformance of our preferred predictive model over the autoregressive models in the in-sample period majorly. This suggests the sensitivity of the result to sample periods, as our predictive model seem to do better when the estimation sample is large.

Table 11: Diebold and Mariano Test Results

Forecast Horizon	FULL				COVID			
	1% tail risk		5% tail risk		1% tail risk		5% tail risk	
	Brent	WTI	Brent	WTI	Brent	WTI	Brent	WTI
Pane 1: Distributed Lag Model versus AR(1) Model Comparison								
USD/GBP								
In-Sample	-178.89***	-264.41***	-210.93***	-334.16***	-3.87***	0.90	-2.88***	-3.47***
$h=15$	-35.88***	-55.73***	-43.59***	-69.14***	-1.03	0.14	-1.28	-0.98
$h=30$	-27.16***	-41.97***	-33.57***	-53.31***	-0.95	0.02	-1.24	-0.95
$h=60$	-22.03***	-33.86***	-27.75***	-44.16***	-1.19	-0.14	-1.53	-1.14
USD/CAD								
In-Sample	-601.83***	-393.84***	-597.34***	-281.18***	1.51	7.47***	0.97	3.41***
$h=15$	-117.94***	-75.77***	-119.11***	-57.02***	0.23	1.44	0.38	1.00
$h=30$	-86.65***	-55.07***	-89.43***	-43.35***	0.10	1.09	0.28	0.83
$h=60$	-68.24***	-41.82***	-73.33***	-35.10***	-0.06	0.93	0.16	0.75
USD/JPY								
In-Sample	-121.06***	-90.90***	-477.32***	-38.76***	-1.29	-7.47***	1.24	-5.51***
$h=15$	-24.48***	-18.29***	-99.79***	-8.34***	-0.47	-1.73*	0.66	-1.41
$h=30$	-18.81***	-13.88***	-72.57***	-6.82***	-0.49	-1.47	0.60	-1.27
$h=60$	-15.76***	-11.55***	-53.86***	-6.25***	-0.65	-1.47	0.53	-1.34
Pane 2: Distributed Lag Model versus AR(2) Model Comparison								
USD/GBP								
In-Sample	-185.23***	-269.45***	-220.85***	-342.02***	-3.86***	0.28	-2.88***	-4.61***
$h=15$	-37.19***	-57.52***	-45.83***	-71.04***	-1.03	-0.04	-1.28	-1.27
$h=30$	-28.18***	-43.24***	-35.42***	-55.00***	-0.95	-0.13	-1.24	-1.20
$h=60$	-22.54***	-34.84***	-28.70***	-45.93***	-1.18	-0.30	-1.52	-1.40
USD/CAD								
In-Sample	-579.80***	-385.77***	-575.67***	-278.16***	1.36	7.32***	0.92	3.30***
$h=15$	-113.07***	-74.14***	-114.07***	-56.31***	0.20	1.41	0.36	0.97
$h=30$	-82.69***	-53.84***	-85.09***	-42.72***	0.08	1.07	0.26	0.80
$h=60$	-64.42***	-40.77***	-67.60***	-34.46***	-0.09	0.91	0.14	0.72
USD/JPY								
In-Sample	-122.53***	-91.42***	-537.91***	-38.88***	-2.29**	-8.89***	1.13	-6.54***
$h=15$	-24.81***	-18.41***	-115.28***	-8.37***	-0.71	-2.03**	0.61	-1.66*
$h=30$	-19.09***	-13.97***	-83.92***	-6.85***	-0.69	-1.71*	0.55	-1.48
$h=60$	-15.84***	-11.45***	-56.79***	-6.19***	-0.84	-1.70*	0.49	-1.55

Note: Each cell in the table contains the Diebold and Mariano test Statistics comparing our WN-type distributed lag model with autoregressive models lags one (Pane 1) and two (Pane 2). The statistical significance of the test at 1%, 5% and 10% is denoted by ***, ** and *, respectively.

Table 12: Model Confidence Sets

Forecast Horizon	Model	Full				COVID			
		1% tail risk		5% tail risk		1% tail risk		5% tail risk	
		Brent	WTI	Brent	WTI	Brent	WTI	Brent	WTI
					USD/GBP				
In-Sample	$AR(1)$	0.17136 [1]	0.17136 [1]	0.11057 [1]	0.11057 [1]	-	0.19605 [1]	-	-
	$AR(2)$	0.17137 [2]	0.17137 [2]	0.11062 [2]	0.11062 [2]	-	0.19624 [2]	-	-
	DL	0.17842 [3]	-	-	-	0.12979 [1]	0.20789 [3]	0.12526 [1]	0.14547 [1]
$h=15$	$AR(1)$	0.17140 [1]	0.17140 [1]	0.11038 [1]	0.11045 [1]	-	0.18838 [1]	-	-
	$AR(2)$	0.17141 [2]	0.17141 [2]	0.11050 [2]	0.11050 [2]	-	0.18850 [2]	-	-
	DL	-	-	-	-	0.13409 [1]	0.20716 [3]	0.12254 [1]	0.14202 [1]
$h=30$	$AR(1)$	0.17118 [1]	0.17118 [1]	0.11020 [1]	0.11028 [1]	-	0.17928 [1]	-	-
	$AR(2)$	0.17119 [2]	0.17119 [2]	0.11032 [2]	0.11032 [2]	-	0.17940 [2]	-	-
	DL	-	-	-	-	0.12880 [1]	0.19815 [3]	0.11681 [1]	0.13553 [1]
$h=60$	$AR(1)$	-	-	0.10982 [1]	0.10999 [1]	-	0.18325 [1]	-	-
	$AR(2)$	0.17061 [1]	0.17061 [1]		0.11004 [2]	-	0.18357 [2]	-	-
	DL	-	-	-	-	0.12323 [1]	0.18610 [3]	0.10609 [1]	0.12299 [1]
					USD/CAD				
In-Sample	$AR(1)$	-	-	-	-	-	0.15198 [2]	0.07974 [3]	0.07974 [2]
	$AR(2)$	0.23703 [1]	0.23703 [1]	0.10670 [1]	0.10670 [1]	-	0.14914 [1]	0.07754 [2]	0.07754 [1]
	DL	-	-	-	-	0.09169 [1]	0.28963 [3]	0.07413 [1]	0.12347 [3]
$h=15$	$AR(1)$	-	-	-	-	-	0.14712 [2]	0.07611 [3]	0.07611 [2]
	$AR(2)$	0.23662 [1]	0.23667 [1]	0.10652 [1]	0.10652 [1]	-	0.14443 [1]	0.07407 [2]	0.07407 [1]
	DL	-	-	-	-	0.08676 [1]	0.27310 [3]	0.07002 [1]	0.11654 [3]
$h=30$	$AR(1)$	-	-	-	-	-	0.14384 [2]	0.07260 [3]	0.07260 [2]
	$AR(2)$	0.23622 [1]	0.23635 [1]	0.10634 [1]	0.10634 [1]	-	0.14128 [1]	0.07068 [2]	0.07068 [1]
	DL	-	-	-	-	0.08209 [1]	0.25832 [3]	0.06641 [1]	0.11052 [3]
$h=60$	$AR(1)$	-	-	-	-	-	0.13665 [2]	0.06756 [3]	0.06756 [2]
	$AR(2)$	0.23541 [1]	0.23554 [1]	0.10598 [1]	0.10598 [1]	-	0.13431 [1]	0.06585 [2]	0.06585 [1]
	DL	-	-	-	-	0.07531 [1]	0.23407 [3]	0.06030 [1]	0.10003 [3]
					USD/JPY				
In-Sample	$AR(1)$	0.19127 [2]	0.19127 [2]	0.07189 [1]	0.07189 [1]	-	0.18104 [2]	-	-
	$AR(2)$	0.19126 [1]	0.19126 [1]	0.07191 [2]	0.07191 [2]	-	0.17257 [1]	-	-
	DL	-	-	-	-	0.12371 [1]	0.72658 [3]	0.04095 [1]	0.04448 [1]
$h=15$	$AR(1)$	0.19114 [2]	0.19114 [2]	0.07190 [1]	0.07190 [1]	-	0.17374 [2]	-	-
	$AR(2)$	0.19113 [1]	0.19113 [1]	0.07191 [2]	0.07191 [2]	-	0.16569 [1]	-	-
	DL	-	-	-	-	0.11674 [1]	0.68503 [3]	0.03865 [1]	0.04198 [1]
$h=30$	$AR(1)$	0.19107 [2]	0.19107 [2]	0.07194 [1]	0.07194 [1]	-	0.16858 [2]	-	-
	$AR(2)$	0.19107 [1]	0.19107 [1]	0.07196 [2]	0.07196 [2]	-	0.16084 [1]	-	-
	DL	-	-	-	-	0.11047 [1]	0.64802 [3]	0.03665 [1]	0.03984 [1]
$h=60$	$AR(1)$	0.19099 [2]	0.19099 [2]	0.07205 [2]	0.07205 [2]	-	0.16113 [2]	-	-
	$AR(2)$	0.19042 [1]	0.19042 [1]	0.07171 [1]	0.07171 [1]	-	0.15379 [1]	-	-
	DL	-	-	-	-	0.09990 [1]	0.58511 [3]	0.03332 [1]	0.03629 [1]

Note: The figures in each cell represent the estimated loss associated with each model with their corresponding ranks in square brackets. The cell containing hyphen are cases where the corresponding model has been eliminated from the model set, on the basis of its underperformance in comparison with the contending models. AR1 and AR2 are Autoregressive models with one and two lags, respectively; while DL denotes our Westerlund and Narayan type distributed lag model. The reported figures are based on 80% randomly selected models from a bootstrap sample of 5000.

On the model confidence set, the stance is different. We find that our predictive model is eliminated from the superior model set in most cases under the full sample period, with the AR(1) and AR(2) models alternately outperforming the other contending models across the exchange rate pairs, oil proxies, tails risks and forecast horizon. However, the stance of outperformance changed under the COVID period, where our predictive distributed lag model consistently dominated in most cases (see right hand pane on Table 12), across the forecast horizons and exchange rate pairs, irrespective of the oil proxies and tail risk except for WTI at 1% tail risk. The predictive performance of our model under the Diebold and Mariano test are in contrast with the performance under the model confidence set, we have a confirmation of the relative importance of oil tail risk for exchange rate tail risks; though sensitive to length of estimation period.

5. Conclusion

We evaluate the possible connection between the oil tail risk and three USD currency pairs (i.e., USD/GBP, USD/CAD and USD/JPY) tail risks where the four variants (Adaptive, Symmetric absolute value, Asymmetric slope and Indirect GARCH) of the Conditional Autoregressive Value at Risk (CAViaR) of Engle & Manganelli (2004) are estimated from which the best tail risk is distinctly obtained for the predicted and the predictor series. We utilize the available daily data over the period of 1987 and 2021 with over 8000 observations and preliminary statistics rendered depict evidence of heavy tails for the return series of both oil price and the three exchange rate pairs. Consequently, we construct a predictive model where oil tail risk serves as a predictor for the exchange rates tail risks and employ the approach of Westerlund & Narayan (2012, 2015) which accounts for some salient features typical of oil and exchange rate (Salisu et al., 2019a; Salisu et al., 2020). Our results for USD/GBP and USD/CAD show a strong connection between the two tail risks for both 1% and 5% VaRs and regardless of the choice of oil price proxy, thus suggesting that downturns in the oil market are capable of causing instabilities in the U.S. Dollar market. For USD/JPY on the other hand, our results indicate an inverse relationship between oil tail risk and the exchange rate tail risk, albeit at 5% VaR, signifying that this currency pair could serve as a good hedge against oil market instability. The results leading to these conclusions are robust to alternative magnitudes of VaR, sample periods and multiple forecast horizons. Investors seeking to maximize returns in the U.S. foreign exchange market may find the results insightful, particularly, in terms of the possible risk aversion and the choice between the two risky assets, an area that can be further investigated by future studies.

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