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Risk Measure between Exchange Rate and Oil Price during Crises: Evidence from Oil-Importing and Oil-Exporting Countries

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Abstract: This study investigates the risk spillover effect between the exchange rate of importing and exporting oil countries and the oil price. The analysis is supported by the utilization of a set of double-long memories. Thereafter, a multivariate GARCH type model is adopted to analyze the dynamic conditional correlations. Moreover, the Gumbel copula is employed to define the nonlinear structure of dependence and to evaluate the optimal portfolio. The conditional Value-at-Risk (CoVaR) is adopted as a risk measure. Findings indicate a long-run dependence and asymmetry of bidirectional risk spillover among oil price and exchange rate and confirm that the risk spillover intensity is different between the former and the latter. They show that the oil price has a stronger spillover effect in the case of oil exporting countries and the lowest spillover effect in the case of oil importing countries.

Keywords: oil imports/exports; exchange rate; risk management; ΔCVaR; optimal hedge ratio; quantile regression

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1. Introduction and Literature Review

The relation between oil prices and the exchange rate has been extensively researched, with substantial evidence of such behavior documented in several economic and financial studies. On the other hand, crude oil plays an important economic role because of its utilization in production and consumption. On the other hand, the exchange rate is considered a crucial indicator of a country's trade competitiveness (Turhan et al. 2014).

There is substantial notice in analyzing the dependence structure among the oil market and exchange market in oil-importing and oil-exporting countries. In fact, by transferring income from oil imports to oil exports, the oil price impacts the country's wealth through a change in the terms of trade and the way exchange rates are impacted (Szturo et al. 2021).

Indeed, unexpected oil price variation may be diffused to the exchange rate via the channel of the terms of trade and the channel of wealth effects. For the first one, a negative value lowers the price of non-traded goods in the domestic economy and thus the real exchange rate. As a consequence, the adjustment of the real exchange rate implies nominal exchange rate depreciation. For the second one, there is a transmission of wealth from oil producers to oil consumers, leading to an important modification in current account balances and portfolio reallocation. As a consequence, the real exchange rate has to appreciate after an unexpected negative variation in the oil price (Kilian 2009).

As market players are exposed to price variability, they are confronted with risk and must thus safeguard their gains. Their primary goal is to ensure the lowest predicted expenses for the expected oil price. As a result, they can use risk management approaches to limit risk while optimizing profits with the aim of coping with price risk. In this regard, concerning the oil price, the development of the best exact risk measurement modelization has emerged as a key problem for better risk management in this context

(Roubaud and Arouri 2018). Especially, the connection between oil markets and exchange markets relies on the economic position of oil-importing versus oil-exporting countries. Given the consequences of a modification in oil prices on energy prices, the movement of such a relation presents important information. Investors, households, and market participants can profit from such evidence in planning their expenditures (Nandelenga and Simpasa 2020).

These empirical findings have prompted scholars to examine the link between oil price shocks and exchange rates. In this regard, Yang et al. (2017) study the comovement between the oil price and the exchange rate by using the wavelet coherence framework. Results confirm that robust interdependence is restricted to the oil-importing countries. Furthermore, they note a negative connection with oil-exporting countries.

Kocoglu et al. (2023) examine the impact of oil price variations on the exchange rates. They refer to the time-varying Granger causality model. The results indicate heterogenous impacts of the oil price on the exchange rate at different time horizons. Geng and Guo (2022) examine the spillover effect of two exogenous variables, VIX and oil price, on the exchange rate volatility. The estimation shows that VIX's spillover effect on the whole Belt and Road exchange rate volatility network varies inversely after the introduction of the Belt and Road Initiative in the short and long term. Wang and Xu (2022) examine the bidirectional spillover effect among the exchange rates of emerging market countries and the international crude oil price. Results confirm the existence of bidirectional risk spillovers among crude oil prices and the exchange rates of emerging market countries.

Isah and Ekeocha (2023) verify how modifications in oil prices impact the dynamics of exchange rates during crisis periods. They hypothesized that the potential of oil prices as an amplifier of exchange rate volatility during crises varies for economic and non-economic crises with divergent origins. They confirm that the divergent origins of different crises matter and can increase exchange rate volatility. Wang et al. (2022) use a dynamic factor model to correctly describe the dynamic dependence and risk spillovers among the crude oil and exchange rate returns of oil-trading countries. They confirm that the factor-copula model can detect the dynamic structure among crude oil and exchange rate markets more precisely than the traditional Copula–GARCH model. Results also show the absence of conditional risk spillover from exchange rates to crude oil prices.

Kumeka et al. (2022) adopt a panel Vector Autoregressive model. Results confirm that a shock to crude oil prices implies a negative reaction in exchange rates in the post-coronavirus pandemic. They conclude that before the coronavirus pandemic, different exporting oil countries were just impacted by their market fundamentals and evolutions. Sadeghi and Roudari (2022) confirm that the reactions of oil-producing countries are remarkably similar to each other and different from those of oil-consuming ones. Candila et al. (2021) investigate the relationship between the oil returns and exchange rate among oil-exporting and oil-importing countries. They refer to the dynamic conditional correlation mixed-data sampling (DCC-MIDAS) model. Results show that before and after the COVID-19 crisis, the long-run correlations of the oil-exporting countries powerfully increased. As to the oil-importing countries, before this crisis, the correlations were negative. After that, they increased.

Mensi et al. (2022) examine the risk spillovers between the spot prices of West Texas Intermediate crude oil and exchange rates. The findings show a connectedness between these markets and that exporters are net transductors of volatility. Heru et al. (2023) examine the long- and short-term effects of the oil price on the Indonesian exchange rate. They refer to the error correction model. The findings show a non-significant positive connection between oil prices and the exchange rate in the long term and a significant positive connection in the short term.

Shang and Hamori (2021) investigate the daily time-varying connection among the foreign exchange rates of oil-importing and oil-exporting countries. Their results indicate that the oil price has more spillover effects on the exchange rates. Ahmad and Hernandez (2013) examine the relationship and asymmetric adjustment among oil prices and the exchange rates of oil importing and exporting countries. Their results show the presence of cointegration and asymmetric adjustment in producer oil countries. Chatziantoniou et al. (2023) examine contagion dynamics among diverse types of oil price shocks and exchange rates. Results show that oil shock net spillovers composed most of the net connectedness values in majority countries through the pre-COVID-19. Equally oil exporting and oil importing countries were all net receivers of shocks. But, during the COVID-19 era, there were important differences.

Wen et al. (2020) explore the link between oil prices and exchange rates by distinguishing between oil producers and oil-consuming countries. They confirm the existence of spillover effects, which are much higher for the oil-producers than the consumers. To investigate the cross-spectral coherence and co-movement among West Texas Intermediate and the exchange rate, Kyophilavong et al. (2023) refer to the quantile cross-spectral approach. Results reveal negative spillover impacts and highlight the absence of co-movements at high frequency. Huang and Li (2022) examine the dynamic spillover effect of crude oil price variation on China's real effective exchange rate. Oil price variations impact China's exchange rate movements. Findings demonstrate that shocks to crude oil prices have a dynamic negative spot impact on the exchange rate.

Korley and Giouvris (2022) explore the joint effect of oil price and oil volatility by employing quantile regression and Markov switching models. They confirm that oil volatility shocks significantly impact the exchange rate for oil-importing and oil-exporting countries, while oil price shocks only impact the oil-consuming ones. Using the autoregressive distributed lag model and the error correction model, Mohammed Suliman and Abid (2020) show the existence of a strong long-term cointegration. With the aim of examining the multivariate dependence among oil prices and exchange rates for the case of oil consumer and oil producer countries, Chkir et al. (2020) use the copulas approach. They conclude that oil can wait as a poor hedge versus exchange rates.

The concept of spillover risk is of great importance for oil risk management and policymakers' decisions. Nonetheless, this analysis examines volatility spillovers between the oil price and exchange rate. It has two purposes. Firstly, by using a $DCC - GARCH$ model, it examines the asymmetric volatility transmission among oil prices and exchange rates of oil import and export countries. A bivariate $cDCC - FIGARCH$ process and Gumbel copula model are also adopted. This allows us to look at the short- and long-term linkages among oil and the exchange rate, as well as the volatility spillover impact across both markets, all at the same time.

Secondly, this paper demonstrates the consequences of the findings linked to the transfer of volatility between examined imported and exported oil countries in the context of an optimal portfolio strategy, oil risk hedging, and hedging efficiency by developing a risk-minimizing portfolio free of reducing projected returns. For this purpose, an $CVaR$ approach is adopted (see Girardi and Ergün (2013)) to investigate the risk spillovers among oil price and exchange rate from the perspective of intense risks with the aim of investigating the impact of crude oil price fluctuations on the exchange rate and exploring the correlation structures among oil return variations and exchange rate.

A hedged portfolio is constructed in which an investor proposes to hedge exposure to intense oil price variations. Precisely, the optimal weights of a hedged portfolio that consists of Brent crude oil futures contracts and each of the exchange rate futures are computed, and the optimal hedge ratio and the hedging efficiency are determined. Furthermore, the importance of Brent oil futures as a hedging and safe-haven asset pending downward trends in the exchange rate is explored.

As well, a $\Delta CVaR$ measure is implemented. It characterizes the modification from the $CVaR$ under troubled state and the $CVaR$ in a benchmark state. For a more detailed analysis, the entire sample is divided into importing and exporting oil countries, and the entire series data are broken down for the period into numerous sub-periods, each of which belongs to a particular market turbulence event, such as the global financial crisis, the

European sovereign debt crisis, the economic recovery period, the recent oil price crash, and the coronavirus pandemic during different important economic and financial events.

In this context, Ji et al. (2019) examine the dynamic dependence between WTI crude oil and the exchange rates of the United States and China. Conditional Values-at-Risk are used to measure the rising and failing risk dependencies among oil prices and exchange rates. The findings of conditional Values-at-Risk illustrate the existence of a meaningful spillover risk from crude oil to the Chinese and American exchange rate markets. On the other side, Mensi et al. (2017) study the dependence structures among oil and currency markets in MENA by employing variational mode decomposition. They evaluate the decrease and increase of risk spillovers from oil to the U.S. in a medium- and short-term context by calculating the conditional Value-at-Risk measures. Results show the evidence of upwards and downwards asymmetric systemic risks, from oil to exchange rates.

As well as Liu et al.'s (2020) investigation of the extreme risk comovement of oil price and exchange rates in oil importing and exporting countries. They refer to time-varying copula models and tail dependencies to evaluate the decrease and increase in conditional value-at-risk measures. Their CoVaRs results show a significant risk correlation between crude oil returns and exchange rates. Within the same analytical framework, Tiwari et al. (2019) study the dependence structure and systemic risk among the return series of the prices of crude oil and the BRICS exchange rates to the U.S., applying specifically the nonparametric conditional Value-at-Risk Granger causality test. Their results show a negative dependence in the long-run dynamics between oil prices and Brazilian, Indian, and South African currencies.

Thereafter, this paper is planned in this way. The econometric technique, which incorporates the generalized long memory model for conditional mean modeling, is presented in Section 2. Furthermore, it exemplifies the multivariate conditional volatility, the dynamic conditional correlations modeling, and the Gumbel copulas. The VaR, $CVaR$, and $\Delta CVaR$ measure the severe risk spillover effect between the exchange rate and the crude oil price. The empirical framework, as well as portfolio strategies and hedging methods, are discussed in Section 3. The last section concludes the paper.

2. Methodology

In this study, the multivariate $GARCH$-copula-$CVaR$ model is implemented to investigate the risk spillover effect between the exchange rate and the oil price by distinguishing the cases of oil importing and exporting countries. The optimal model is initially constructed and $\Delta CVaR$ is accordingly adopted to describe the intense risk spillover effect between the exchange rate and the oil price.

The econometric specification used in this analysis has three parts. First, a long memory model is estimated. Afterward, this study is adopted to estimate the unconditional VaR related to each exchange rate series. Further, to model the conditional variance, a multivariate $GARCH$ model is used. Then, the corrected dynamic conditional correlation model is used to analyze the spillover of volatility among the oil returns and exchange rate returns. In addition, the nonlinear structure of dependence is investigated by falling back on Archimedean copula functions with different tail dependence structures, specifically Gumbel, Clayton, and Frank. In this research, Gumbel copulas are used, which are capable of detecting asymmetric tail dependence. Hence, the estimated residuals are used to compute the conditional VaR $(CVaR)$ and the $\Delta CVaR$ to gauge the size of potential tail spillover effects from the oil market to each exchange rate.

This analysis suggests the use of the oil price future as a diversifier and hedge investment for the exchange rate in emerging markets. The consequences for optimal design and hedging strategies are built on the optimal portfolio weights (ω); the optimal hedge ratio (β); and the hedge effectiveness index (HE).

2.1. Generalized Long-Memory Model

The Generalized Autoregressive Moving Average ($GARMA$) model or k -frequency $GARMA$ process is a subclass of long memory models. The following are the definitions for various frequency models:

$$\Phi(L)\prod_{i=1}^{k}\left(I-2\nu_i L+L^2\right)^{d_i}(y_t-\mu)=\Theta(L)\varepsilon_t \tag{1}$$

where $\Phi(L)$ and $\Theta(L)$ are the polynomials of delay operator L. The parameters ν_i, $|\nu_i|<1$, $i=1,\ldots,k$, offer data about mobility on a regular basis in the conditional mean, ε_t is a white noise perturbation sequence with variance σ_ε^2, k is a finite integer, are conditional mean long memory characteristics that indicate how autocorrelations are gradually muted, μ is the mean of the process, and $\lambda_i=\cos^{-1}(\nu_i)$, $i=1,\ldots,k$, represent the Gegenbauer frequencies. For a single frequency $GARMA$ model with, when $\nu=1$ (i.e., $\lambda=0$), the model is reduced to a $ARFIMA$ model. Granger and Joyeux (1980) and Hosking (1981) present it as a parametric tool for capturing long-range dependent dynamics. It's a cost-effective way to predict the long-term behavior of time series. $ARFIMA(p,\ d,\ q)$ process is presented as:

$$\Phi(L)(1-L)^d(y_t-\mu)=\Theta(L)\varepsilon_t \tag{2}$$

where, ε_t is a white noise process, with zero mean and variance σ^2.

2.2. Time-Varying Volatilities

A fractional filter in the equation of conditional variance is used to extend the generalized long-memory process and duplicate similar patterns. In this context, we propose the Fractional Integrated Generalized Autoregressive Conditional Heteroscedasticity ($FIGARCH$) type innovations, which permit to calculate their time-varying standard deviations and evaluate the long memory behavior in the conditional variance (Boubaker and Boutahar 2011; Boubaker and Sghaier 2015; and Bagchi and Biswajit 2023).

The following is how the variance equation is modeled:

$$\varepsilon_t=(\varepsilon_{1t},\ \ldots,\ \varepsilon_{kt})'=H_t^{\frac{1}{2}}\xi_t \tag{3}$$

where

$$\varepsilon_t\mid\Psi_{t-1}\ \sim\ D\ (0,\ H_t)\ and\ \eta_t\ \sim\ D(0,\ I_k) \tag{4}$$

with

$$H_t=E\left(\varepsilon_t\varepsilon_t{}'\mid\Psi_{t-1}\right) \tag{5}$$

Here, Ψ_{t-1} is the information set a time $t-1$, $D(\cdot)$ is a multivariate density function using the mean vector and dynamic conditional covariance matrix as inputs. ε_t is the residual term from the mean equations, ξ_t is a $(k\times 1)$ vector of i.i.d. errors, and H_t is the conditional covariance matrix.

The $DCC-GARCH$ specification of the covariance matrix, H_t, can be expressed as:

$$H_t=D_tR_tD_t \tag{6}$$

where $D_t=diag\left(\sqrt{h_{1,\,t}},\ \ldots,\ \sqrt{h_{k,\,t}}\right)$ is a $k\times k$ diagonal matrix of time-varying standard deviations from $FIGARCH$ models defined as:

$$h_{i,\,t}=\ \omega_i{}^*\ +\ \left[1-(1--(L)\right]^{-1}\Psi_i(L)\left(1-L\right)^{\delta}\varepsilon_{i,\,t}^2 \tag{7}$$

where $i=1,\ \ldots,\ k$, $\Psi_i(L)=1-\sum_{m=1}^{r}\psi_{im}L^m$ and $B_i(L)=1-\sum_{m=1}^{s}\beta_{im}L^m$ are suitable polynomials in the lag operator whose roots are distinct and lie outside the unit circle, $\omega_i{}^*>0$, $0<\delta<1$ is the fractional differencing parameter, and $R_t=\{\rho_{ij}\}$ is the time-varying conditional correlation matrix.

The approximation procedure of $DCC - FIGARCH$ model is constructed on two steps. In the initial phase, a univariate $FIGARCH$ model is assessed. In the next phase, the vector of standardized residuals $\xi_{i,\,t} = \hat{\varepsilon}_{i,\,t} h_{i,\,t}^{\frac{-1}{2}}$ is used to progress the DCC correlation specification as:

$$R_t = diag\left(q_{11,\,t}^{-\frac{1}{2}},\ \ldots,\ q_{kk,\,t}^{-\frac{1}{2}}\right) Q_t\ diag\left(q_{11,\,t}^{-\frac{1}{2}},\ \ldots,\ q_{kk,\,t}^{-\frac{1}{2}}\right) \tag{8}$$

where $Q_t = \left(q_{ijt}\right)$ is a symmetric positive define matrix. Q_t is supposed to change along with a $GARCH$ -type process as

$$Q_t = (1 - \theta_1 - \theta_2)\overline{Q} + \theta_1 \xi_{t-1} \xi_{t-1}^{'} + \theta_2 Q_{t-1} \tag{9}$$

The parameters θ_1 and θ_2 are scalar parameters to detect the effects of precedent shocks and dynamic conditional correlation on current dynamic conditional correlation. These parameters are assumed to be nonnegative and satisfying $\theta_1 + \theta_2 < 1$. $\overline{Q}$ is an $k \times k$ unconditional variance matrix of standardized residuals $\xi_{i,\,t}$. The correlation estimators of the preceding equation are given by:

$$\rho_{ij,\,t} = \frac{q_{ij,\,t}}{\sqrt{q_{ii,\,t} q_{jj,\,t}}} \tag{10}$$

The $cDCC$ which has a similar measurement as the DCC model except for the correlation process Q_t as described in Equation (9), is reformulated by switching ξ_t by $\xi_t^* = diag\{Q_t\}^{\frac{1}{2}} \xi_t$.

2.3. Dependence Tail-Copula Model

The copula-based $MGARCH$ model outlines the dependence structure and the conditional correlation distinctly and instantly. The former is controlled by a copula function, and the latter is modeled by an $MGARCH$ model for H_t. The capacity of a copula function to simulate conditional correlation and dependency independently and concurrently for interested series with non-elliptically distributed dependent errors is its most distinguishing feature.

For a random vector $\xi_t = (\xi_{1t}, \ldots, \xi_{dt})^{'} \in \mathbb{R}^d$, with a joint distribution function F and continuous marginals $F_1, \ldots, F_d$, $d \geq 2$, Sklar's theorem guarantees the presence of a single function $C : [0,1]^d \to [0,1]$, termed the copula, implying equality:

$$C(u_{1t}, \ldots, u_{dt}) = F\left(F_1^{-1}(u_{1t}), \ldots, F_d^{-1}(u_{dt})\right) \tag{11}$$

where F_i^{-1} represents the generalized inverse of F_i given as

$$F_i^{-1}(u_{it}) \equiv q_i^{u_{it}} = inf\{\xi_{it} | F_j(\xi_{it}) \geq u_{it}\} \tag{12}$$

In this study, we use Archimedean copula functions with diverse tail dependency structures, such as Gumbel (upper tail dependence), Clayton (lower tail dependence), and Frank (lower tail dependence), to examine the nonlinear structure of dependence (symmetric dependence). Gumbel copulas are members of the Archimedean copula family that may capture extreme-value correlation structures. We employ Gumbel copulas in our study, which are most commonly used in risk analysis and are valuable because they can capture asymmetric tail dependency (Tian et al. 2023; Mensi et al. 2023; Wang et al. 2023)

To describe an asymmetric dependency structure, the Gumbel copula is chosen. This copula is defined by:

$$C_G(u_{1t}, \ldots, u_{dt}) = exp\left(-\left[(-ln(u_{1t}))^{\lambda} + \cdots + (-ln(u_{dt}))^{\lambda}\right]^{\lambda^{-1}}\right),\ \ \lambda \geq 1 \tag{13}$$

The inference functions for margins (IFM) method suggested by Joe and Xu (1996) is used in this work. Frequently, the following logarithmic maximum likelihood function is employed to estimate the parameter of the copula:

$$L_T(\zeta;U) = \sum_{t=1}^{T}\left(Log\{c(F_1(u_{1t};\ \zeta_1),\ \ldots, F_d(u_{dt};\ \zeta_d)\ ;\ \lambda)\} + \sum_{i=1}^{d} Log\{f_i(u_{it}\ ;\ \zeta_i)\}\right) \tag{14}$$

where $\zeta = (\zeta_i,\ \lambda)$ is the vector that contains the marginal parameters ξ_i and copula parameters λ.

Consequently, the estimation process of ζ, noted $\hat{\zeta}_{IFM} = (\hat{\zeta}_i,\ \hat{\lambda}_{IFM})$ is performed in two phases. In a first phase, the parameter vector of conditional marginal distribution is estimated as:

$$\hat{\zeta}_i = \underset{\zeta_i}{Arg\ max} \sum_{t=1}^{T} Log\{f_i(u_{it}\ ;\ \zeta_i)\} \tag{15}$$

In a second phase, the copula parameters λ are estimated as follows:

$$\hat{\lambda}_{IFM} = \underset{\lambda}{Arg\ max} \sum_{t=1}^{T} Log\{c(F_1(u_{1t}\ ;\ \hat{\zeta}_1),\ \ldots, F_d(u_{dt}\ ;\ \hat{\zeta}_d)\ ;\ \lambda)\} \tag{16}$$

2.4. Conditional Value-at-Risk Models

The Value-at-Risk (VaR) is an aggregated assessment of a portfolio of contracts and assets' overall risk. Within a certain confidence interval, it describes the projected maximum loss of a portfolio over a desired horizon (generally 95 percent). Therefore, VaR is a monetary unit of measurement. Relying on VaR is a good indicator of minimizing portfolio risk (Lee et al. 2023; Mo et al. 2023).

Agreed the return R_t^i of a specific market i at time t with a confidence level of q; $VaR_t^{i,q}$ is implicitly defined as q^{th} quantile. The following is the return distribution:

$$P\left(R_t^i \leq VaR_t^{i,q}\right) = q \tag{17}$$

where $VaR_t^{i,q}$ is typically a negative number.

The key disadvantage of this strategy is that it fails to identify prospective losses over the value of VaR. To overcome this limit, the conditional Value-at-Risk $CVaR$ method was adopted (Artzner et al. 1999; Hanif et al. 2023). It is based on a weighted average of higher-probability losses compared to VaR. Thus, the robustness of the results is strengthened with the $CVaR$ modeling. On the other hand, the conditional Value-at-Risk at the level α denoted $CVaR(\alpha)$ illustrates the conditional expected portfolio losses beyond the $VaR(\alpha)$ level. The $CVaR$ confirms well-matched econometric properties compared to VaR since it considers the thick tails in the portfolio loss distribution. According to Girardi and Ergün (2013), $CVaR_{q,t}^{s/i}$ is calculated as the q -quantile of the conditional distribution given as:

$$P\left(R_t^s \leq CVaR_{q,t}^{s/i} / R_t^i \leq VaR_{q,t}^{s/i}\right) = q \tag{18}$$

This change permits more extreme losses. Along these lines, Tobias and Brunnermeier (2016) are followed and $\Delta CVaR$ is defined as

$$\Delta CVaR_t^{s/i,q} = CVaR_t^{s/i,q} - CVaR_t^{s/b^i,q} \tag{19}$$

We can see that $CVaR$ is an element of calculating $\Delta CVaR$. For this equation, b^i notes the benchmark state, which indicates the one standard deviation event around the mean: $\mu_t^i - \sigma_t^i \leq R_t^i \leq \mu_t^i + \sigma_t^i$, where μ_t^i and σ_t^i note the conditional mean and standard deviation of the system, respectively.

Nonetheless, to determine $CVaR$ the univariate generalized long memory models fixed for oil price and for each exchange rate, it is necessary to estimate isolated time series of *VaRs* oil returns and exchange rate series. Finally, the $CVaR_{q,t}^{s/oil}$ measure for oil returns and exchange rate series at a given time period t is defined as:

$$\begin{aligned} CVaR_{q,t}^{s/i} &= F^{-1}(q)\sigma_t^s\sqrt{1-\sigma_{s/i,t}^2} + F^{-1}(q)\rho_{s/i,t}\sigma_t^s \\ &= VaR_{q,t}^s\sigma_t^s\sqrt{1-\sigma_{s/i,t}^2} + VaR_{q,t}^s\rho_{s/i,t}\sigma_t^s \end{aligned} \tag{20}$$

where $\rho_{s/i,t}$ is the correlation coefficient amongst oil price returns and exchange rate series.

Moreover, $\Delta CVaR_{q,t}^{s/i}$ is adopted, which is labeled "exposure $\Delta CVaR$", to evaluate exchange rate exposure to oil market distress. $\Delta CVaR$ is the difference among its $CVaR$ when oil market is or is not in turmoil (median state) as given formally by:

$$\Delta CVaR_q^{s/oil} = CVaR_q^{s/oil} - CVaR_{50\%}^{s/oil} \tag{21}$$

Since $F^{-1}(50\%) = 0, \Delta CVaR$ can be reduced at each time as:

$$\begin{aligned} \Delta CVaR_q^{\frac{s}{oil}} &= F^{-1}(q)\rho_{s/i,t}\sigma_t^s \\ &= VaR_{q,t}^s\rho_{s/oil,t} \end{aligned} \tag{22}$$

Consequently, a weaker or more positive $\Delta CVaR$ claimed that the exchange market is less exposed to the oil market breakdown.

2.5. Portfolio Designs and Hedging Strategies

The optimal weights of a portfolio that comprises a crude oil-exchange rate pair based on the variance-covariance matrix are estimated to reduce risk without sacrificing expected returns from the *cDCC* and copula models (Kroner and Ng 1998).

$$\omega_{oil,t} = \frac{h_{s;t} - h_{s/oil,t}}{h_{oil,t} + h_{s,t} - 2h_{s/oil,t}} \tag{23}$$

Under the condition that

$$\omega_{s/oil,t}\begin{cases} 0, & \text{if } \omega_{oil,t} < 0 \\ \omega_{oil,t}, & \text{if } 0 \le \omega_{oil,t} \le 1 \\ 1, & \text{if } \omega_{oil,t} > 1 \end{cases} \tag{24}$$

where $\omega_{oil,t}$ mentions to the weight of oil price in a one-dollar portfolio of the two assets well-defined above at a given time t, $h_{s,t}$, and $h_{oil;t}$ are the conditional variances of the exchange rate returns and the oil extreme returns, correspondingly, and $h_{s/oil;t}$ is the conditional covariance among oil and the exchange rate returns at time t. The optimal weight of the exchange rate returns in the measured portfolio is acquired by computing $(1 - \omega_{oil,t})$.

Then, we reflect on the problem of estimating a dynamic risk-minimizing hedge ratio $(\beta_{s/oil,t})$. For reducing the risk of this portfolio, we measure how much a long position (buy) of one-dollar unit in the oil market should be hedged by a short position (sell) of $(\beta_{s/oil,t})$ dollar in the exchange rate, that is:

$$\beta_{s/oil,t} = \rho \times \frac{\sigma_s}{\sigma_{oil}} \tag{25}$$

where σ_s and σ_{oil} are the standard deviations of the exchange rate returns and the oil extreme returns, respectively, and ρ is the correlation between the oil market return and the exchange rate return.

Lastly, the effectiveness of hedging (HE) of portfolio diversification is examined. HE across constructed portfolios (proposed by Ederington (1979)) can be evaluated as

$$HE = 1 - \frac{Var_{hedged}}{Var_{unhedged}} \tag{26}$$

where, Var_{hedged} and $Var_{unhedged}$ represent the variance of hedged (i.e., oil and exchange rate) and unhedged (i.e., oil) portfolios, respectively. An important hedging-effectiveness (HE) portfolio value implies a well-related investment strategy.

3. Empirical Analysis

3.1. Data Description and Preliminary Statistics

To explore the risk spillover effect between the exchange rate of emerging market countries and the international crude oil price, this study chooses the oil exporting countries: Brazil, China, Malaysia, Mexico, Poland, and Russia, and the oil importing countries: India, South Korea, Thailand, Turkey, and South Africa, for a total of six oil exporting markets and five importing ones as the research object. The idea is to analyze the impact of oil that is exported (which we called an exporting oil country) and oil that is imported by others (an importing oil country) without distinguishing between net exporting and net importing oil countries.

The exchange rate of each country's native currency against the US dollar is the primary study variable. Brazilian Real (BRL), Chinese RMB (CNY), Malaysian Ringgit (MYR), Mexican Peso (MXN), Polish Zloty (PLN), Russian Ruble (RUB), Indian Rupee (INR), South Korean Won (KRW), Thai Baht (THB), New Turkish Lira (TRY), and South African Rand (ZAR) are the currencies and codes for each nation.

Brent crude oil is less impacted by regional supply and demand characteristics than WTI crude oil in the international crude oil pricing structure, allowing it to better reflect global crude oil supply and demand.

As a result, the research variables in this study are the spot price of Brent crude oil and the exchange rates of national currencies versus the US dollar. Each time series covers the period from 1 June 2005 through 2 March 2021, corresponding to $T = 4650$ observations. The selected time frame permits analysis of the impact of various financial and economic conditions. As well, the Brent crude oil spot price data comes from the Wind database, and the currency rates of emerging market nations come from the Bank for International Settlements' official statistics (BIS).

As part of this study, the return series is calculated by subtracting the logarithm differences of two successive prices ($R_t = \Delta LogP_t$) for purposes of ensuring data consistency. In effect, using the log difference might cause the series to become stationary. The unit root tests ADF, PP, and KPSS also support this idea

Furthermore, because periods of low volatility are followed by times of high volatility, the series shows a clustering of volatility. This indicates that ARCH effects are present in the series. As a result, these series are stationary[1] and acceptable for the study's future testing.

Table 1 indicates the descriptive statistics for a time series. This table shows that all series have negative skewness and excess kurtosis, suggesting that the Brent crude oil price and each country's currency rate have asymmetric peaks and thick tails. As a result, we may argue that all prices have a significant imbalance to the left. The presence of nonlinearities in the evolution of returns might explain the observed disparity. The Jarque-Bera test confirms the deviation from normality. Indeed, for all series, this test powerfully rejects the null hypothesis of normality, implying that the lowest and highest values differ in greater numbers from the computed mean.

Table 1. Descriptions of data statistics.

	Mean	Std. Dev	Skewness	Kurtosis	Jarque-Bera	Correlation	ARCH (10)
OIL	0.000	0.073	−1.238	6.879	14894.092 (0.000) ***	1.000	23.653 (0.000) ***
Exchange Rate of Oil-Exporting Countries							
BRL (Brezil)	0.000	0.003	0.098	14.077	15862.3 (0.000) ***	0.045	22.582 (0.033) **
CNY (China)	0.000	0004	0.767	21.259	12876.167 (0.000) ***	0.014	17.562 (0.0000) ***
MXN (Mexico)	0.000	0.002	−0.075	15.867	15786.889 (0.000) ***	0.084	16.148 (0.000) ***
PLN (Poland)	0.000	0.002	0.128	12.153	15976.657 (0.000) ***	0.047	27.105 (0.000) ***
MYR (Malysia)	0.000	0.004	0.757	35.764	17867.145 (0.000) ***	0.038	24.058 (0.000) ***
RUB (Russia)	0.000	0.005	0.167	26.564	17291.785	0.045	27.456 (0.000) ***
Exchange Rate of Oil-Importing Countries							
THB (Thaila,dt)	0.000	0.004	−0.259	37.287	17880.762 (0.000) ***	0.084	12.184 (0.013) **
TRY (Turkey)	0.000	0.002	0.245	12.115	18964.673 (0.000) ***	0.067	17.597 (0.000) ***
ZAR (South Africa)	0.000	0.003	0.186	22.264	6674.453 (0.000) ***	0.054	14.934 (0.000) ***
INR (India)	0.000	0.003	−0.006	13.469	42243.767 (0.000) ***	0.069	19.167 (0.084) *
KRW (South Korea)	0.000	0.028	−0.081	27.563	6301.873 (0.000) ***	0.018	15.576 (0.000) ***

Levels of significance of the Jarque-Bera and ARCH tests are indicated between square brackets, where *** denotes significance at the 1% level, ** denotes significance at the 5% level, and * denotes significance at the 10% level.

For all series, the Ljung-Box test reveals considerable evidence of serial correlation, while the ARCH-LM test reveals heteroskedasticity. An ARCH model type is discovered for each exchange market return owing to heteroskedasticity. Moreover, GPH (Geweke and Porter-Hudak 1983) and LW (Robinson 1995) statistics are used to test for long-range dependency in the conditional mean of returns series. Table 2 shows the same results for three bandwidth levels, confirming the presence of extended memory.

Table 2. GPH and LW tests for series.

	Bandwidth	GPH Test			LW Test		
		$\hat{d}_m$	Standard Error	*p*-Value	$\hat{d}_m$	Standard Error	*p*-Value
Exchange Rate of Oil-Exporting Countries							
OIL	$T^{0.6}$	−0.382 ***	0.085	(0.000)	−0.404 ***	0.060	(0.000)
	$T^{0.7}$	−0.146 ***	0.058	(0.000)	−0.136 ***	0.042	(0.001)
	$T^{0.8}$	−0.267 ***	0.040	(0.000)	−0.299 ***	0.029	(0.000)
BRL	$T^{0.6}$	−0.342 ***	0.085	(0.000)	−0.367 ***	0.060	(0.000)
	$T^{0.7}$	−0.243 ***	0.067	(0.000)	−0.256 ***	0.057	(0.001)

Table 2. *Cont.*

	Bandwidth	GPH Test			LW Test		
		$\hat{d}_m$	Standard Error	*p*-Value	$\hat{d}_m$	Standard Error	*p*-Value
	$T^{0.8}$	−0.291 ***	0.044	(0.000)	−0.279 ***	0.039	(0.000)
CNY	$T^{0.6}$	−0.456 ***	0.045	(0.000)	−0.434 ***	0.052	(0.000)
	$T^{0.7}$	−0.173 ***	0.059	(0.000)	−0.166 ***	0.055	(0.001)
	$T^{0.8}$	−0.285 ***	0.039	(0.000)	−0.269 ***	0.036	(0.000)
MXN	$T^{0.6}$	0.087 ***	0.065	(0.000)	0.094 ***	0.063	(0.000)
	$T^{0.7}$	0.107 ***	0.068	(0.000)	0.106 ***	0.072	(0.000)
	$T^{0.8}$	0.121 ***	0.070	(0.000)	0.133 ***	0.072	(0.000)
PLN	$T^{0.6}$	0.154 ***	0.095	(0.000)	0.148 ***	0.087	(0.000)
	$T^{0.7}$	0.163 ***	0.088	(0.000)	0.166 ***	0.082	(0.000)
	$T^{0.8}$	0.155 ***	0.080	(0.000)	0.158 ***	0.085	(0.000)
MYR	$T^{0.6}$	−0.184 ***	0.035	(0.000)	−0.174 ***	0.037	(0.000)
	$T^{0.7}$	−0.176 ***	0.042	(0.000)	−0.168 ***	0.045	(0.000)
	$T^{0.8}$	−0.185 ***	0.040	(0.000)	−0.169 ***	0.043	(0.000)
RUB	$T^{0.6}$	−0.084 ***	0.075	(0.000)	−0.079 ***	0.076	(0.000)
	$T^{0.7}$	−0.078 ***	0.078	(0.000)	−0.076 ***	0.072	(0.001)
	$T^{0.8}$	−0.095 ***	0.084	(0.000)	−0.099 ***	0.089	(0.000)
Exchange Rate of Oil-Importing Countries							
THB	$T^{0.6}$	−0.124 ***	0.065	(0.000)	−0.144 ***	0.062	(0.000)
	$T^{0.7}$	−0.123 ***	0.066	(0.000)	−0.143 ***	0.065	(0.000)
	$T^{0.8}$	−0.125 ***	0.063	(0.000)	−0.139 ***	0.066	(0.000)
TRY	$T^{0.6}$	0.124 ***	0.082	(0.000)	0.123 ***	0.080	(0.000)
	$T^{0.7}$	0.134 ***	0.089	(0.000)	0.136 ***	0.092	(0.000)
	$T^{0.8}$	0.129 ***	0.091	(0.000)	0.130 ***	0.096	(0.000)
ZAR	$T^{0.6}$	0.084 ***	0.055	(0.000)	0.0891 ***	0.060	(0.000)
	$T^{0.7}$	0.103 ***	0.057	(0.000)	0.106 ***	0.062	(0.000)
	$T^{0.8}$	0.112 ***	0.060	(0.000)	0.123 ***	0.069	(0.000)
INR	$T^{0.6}$	−0.345 ***	0.043	(0.000)	−0.364 ***	0.048	(0.000)
	$T^{0.7}$	−0.186 ***	0.043	(0.000)	−0.163 ***	0.042	(0.000)
	$T^{0.8}$	−0.195 ***	0.024	(0.000)	−0.199 ***	0.026	(0.000)
KRW	$T^{0.6}$	0.084 ***	0.035	(0.000)	0.079 ***	0.038	(0.000)
	$T^{0.7}$	0.113 ***	0.052	(0.000)	0.116 ***	0.053	(0.000)
	$T^{0.8}$	0.125 ***	0.046	(0.000)	0.129 ***	0.049	(0.000)

Levels of significance of the GPH and LW tests are indicated between square brackets, where *** denotes significance at the 1% level.

3.2. Empirical Results and Interpretations

3.2.1. Generalized Long Memory Process for Conditional Mean Modeling

The estimations of the generalized long memory model $(k - factorGARMA)$ are shown in Table 3. The mean estimation consequences specify that the log-return of a few series is estimated using the $k - factorGARMA$ model, which indicates that this series is considered to have periodic long memory behavior. However, the rest of the exchange rate markets, $k - factorGARMA$ model is reduced to $ARFIMA$ model for some series (NXN, NYR, PLN, RUB, and TRY), and to $ARMA$ model for all the other exchange series. Indeed, the $GARMA$ estimation results show that the seasonality can be detected in the frequency domain $\lambda_i = 1/T$; where λ is frequency of the seasonality and T is the period of seasonality. Table 3 demonstrates that the oil price and the exchange rate of oil import and export countries have special statistical properties incorporating some important properties such as long-range dependencies, non-linearity, and multiple seasonalities during different financial and economic circumstances.

Table 3. Mean equation estimation.

Parameters	$\widehat{\phi}$	$\widehat{\theta}$	$\widehat{d}_{m,1}$	$\widehat{d}_{m,2}$	$\widehat{\lambda}_{m,1}$	$\widehat{\lambda}_{m,2}$
OIL	0.326 *** (0.000)	–	0.392 *** (0.000)	0.213 *** (0.000)	0.133 *** (0.000)	0.247 *** (0.000)
Exchange Rate of Oil-Exporting Countries						
BRL	–	–	–	–	–	–
CNY	0.3669 *** (0.000)	−0.2314 *** (0.000)	–	–	–	–
MXN	0.893 *** (0.000)	−0.534 *** (0.000)	0.122 * (0.001)	–	–	–
PLN	0.067 ** (0.018)	–	0.101 * (0.026)_	–	–	–
MYR	0.741 *** (0.000)	−0.167 *** (0.000)	0.095 * (0.031)_	–	–	–
RUB	–	–	0.143 * (0.001)_	–	–	–
Exchange Rate of Oil-Importing Countries						
INR	–	–	–	–	–	–
KRW	0.076 ** (0.002)	–	–	–	–	–
THB	0.0964 ** (0.039)	–	–	–	–	–
TRY	−0.748 *** (0.000)	0.787 *** (0.000)	0.085 * (0.002)_	–	–	–
ZAR	0.212 *** (0.000)	−0.380 *** (0.000)	–	–	–	–

Levels of significance (p-value) are indicated between square brackets, where *** denotes significance at the 1% level, ** denotes significance at the 5% level, and * denotes significance at the 10% level.

3.2.2. The Long Memory Process for Conditional Variance Modeling

The estimations of the long memory GPH and LW tests (Table 4) show that long memory exists in the conditional variance, which necessitates the usage of certain fractionally integrated $FIGARCH$ method.

The conditional variance estimation results (Table 5) show that the variance equations are obtained by $FIGARCH$ model, which permits to evaluate the bivariate $cDCC - FIGARCH$ model, in the next step, among crude oil returns and exchange rate returns. Results show that the parameters $\widehat{\delta}$, $\widehat{\psi}$ and $\widehat{\beta}$ are significantly different from zero. Moreover, the sum of the estimated coefficients of $ARCH$ and $GARCH$, $\widehat{\psi}$ and $\widehat{\beta}$, is close to one. These findings point to the presence of long-range dependency in the conditional mean, as well as time-varying correlations and the volatility process' durability. Furthermore, it is noted that the worldwide oil price and each emerging market country's exchange rate exhibit asymmetric peaks and thick tails, which may be well characterized by a skewed student distribution, based on a parameter estimate.

Table 4. GPH and LW tests for squared residuals.

	Bandwidth	GPH Test			LW Test		
		$\hat{d}_m$	Standard Error	*p*-Value	$\hat{d}_m$	Standard Error	*p*-Value
OIL	$T^{0.6}$	0.456 ***	0.063	(0.000)	0.462 ***	0.065	(0.000)
	$T^{0.7}$	0.461 ***	0.068	(0.000)	0.467 ***	0.069	(0.000)
	$T^{0.8}$	0.468 ***	0.071	(0.000)	0.469 ***	0.072	(0.000)
Exchange Rate of Oil-Exporting Countries							
BRL	$T^{0.6}$	0.386 ***	0.057	(0.000)	0.390 ***	0.059	(0.000)
	$T^{0.7}$	0.392 ***	0.059	(0.000)	0.416 ***	0.063	(0.000)
	$T^{0.8}$	0.397 ***	0.062	(0.000)	0.419 ***	0.066	(0.000)
CNY	$T^{0.6}$	0.564 ***	0.073	(0.000)	0.567 ***	0.072	(0.000)
	$T^{0.7}$	0.568 ***	0.075	(0.000)	0.569 ***	0.076	(0.000)
	$T^{0.8}$	0.611 ***	0.079	(0.000)	0.612 ***	0.078	(0.000)
MXN	$T^{0.6}$	0.527 ***	0.078	(0.000)	0.534 ***	0.076	(0.000)
	$T^{0.7}$	0.530 ***	0.082	(0.000)	0.538 ***	0.079	(0.000)
	$T^{0.8}$	0.532 ***	0.085	(0.000)	0.541 ***	0.082	(0.000)
MYR	$T^{0.6}$	0.541 ***	0.083	(0.000)	0.544 ***	0.081	(0.000)
	$T^{0.7}$	0.546 ***	0.086	(0.000)	0.548 ***	0.085	(0.000)
	$T^{0.8}$	0.551 ***	0.088	(0.000)	0.554 ***	0.086	(0.000)
PLN	$T^{0.6}$	0.434 ***	0.058	(0.000)	0.438 ***	0.052	(0.000)
	$T^{0.7}$	0.436 ***	0.063	(0.000)	0.441 ***	0.056	(0.000)
	$T^{0.8}$	0.439 ***	0.065	(0.000)	0.443 ***	0.061	(0.000)
RUB	$T^{0.6}$	0.681 ***	0.053	(0.000)	0.677 ***	0.051	(0.000)
	$T^{0.7}$	0.683 ***	0.056	(0.000)	0.679 ***	0.052	(0.000)
	$T^{0.8}$	0.685 ***	0.058	(0.000)	0.680 ***	0.055	(0.000)
Exchange Rate of Oil-Importing Countries							
INR	$T^{0.6}$	0.435 ***	0.053	(0.000)	0.456 ***	0.049	(0.000)
	$T^{0.7}$	0.456 ***	0.055	(0.000)	0.462 ***	0.052	(0.000)
	$T^{0.8}$	0.465 ***	0.058	(0.000)	−0.469 ***	0.056	(0.000)
KRW	$T^{0.6}$	0.514 ***	0.062	(0.000)	0.519 ***	0.058	(0.000)
	$T^{0.7}$	0.517 ***	0.065	(0.000)	0.524 ***	0.062	(0.000)
	$T^{0.8}$	0.520 ***	0.066	(0.000)	0.528 ***	0.064	(0.000)

Table 4. *Cont.*

	Bandwidth	GPH Test			LW Test		
		$\hat{d}_m$	Standard Error	*p*-Value	$\hat{d}_m$	Standard Error	*p*-Value
THB	$T^{0.6}$	0.446 ***	0.075	(0.000)	0.448 ***	0.072	(0.000)
	$T^{0.7}$	0.449 ***	0.077	(0.000)	0.454 ***	0.076	(0.000)
	$T^{0.8}$	0.452 ***	0.080	(0.000)	0.458 ***	0.078	(0.000)
TRY	$T^{0.6}$	0.387 ***	0.042	(0.000)	0.389 ***	0.041	(0.000)
	$T^{0.7}$	0.391 ***	0.045	(0.000)	0.393 ***	0.042	(0.000)
	$T^{0.8}$	0.392 ***	0.049	(0.000)	0.396 ***	0.047	(0.000)
ZAR	$T^{0.6}$	0.487 ***	0.082	(0.000)	0.489 ***	0.077	(0.000)
	$T^{0.7}$	0.490 **	0.085	(0.000)	0.493 ***	0.082	(0.000)
	$T^{0.8}$	0.482 ***	0.087	(0.000)	0.496 ***	0.084	(0.000)

Levels of significance of the GPH and LW tests are indicated between square brackets, where *** denotes significance at the 1% level and ** denotes significance at the 5% level.

Table 5. Conditional variance equation estimation.

	FIGARCH(1,δ,1)			
Parameters	$\hat{\psi}$	$\hat{\beta}$	$\hat{\delta}$	***Ln(L)***
OIL	0.174 ** (0.027)	0.654 *** (0.0000)	0.467 *** (0.0000)	3685.654
Exchange Rate of Oil-Exporting Countries				
BRL	0.423 *** (0.000)	0.863 *** (0.000)	0.321 *** (0.000)	6793.851
CNY	0.349 *** (0.000)	0.769 (0.000)	0.340 *** (0.000)	4360.323
MYR	0.419 *** (0.000)	0.786 *** (0.000)	0.321 *** (0.000)	6562.644
MXN	0.317 *** (0.000)	0.695 *** (0.0000)	0.331 *** (0.000)	6631.340
PLN	0.518 *** (0.000)	0.769 (0.000)	0.321 (0.000)	572.831
RUB	0.346 *** (0.000)	0.816 *** (0.000)	0.428 *** (0.0000)	5996.254
Exchange Rate of Oil-Importing Countries				
INR	0.452 *** (0.000)	0.738 *** (0.000)	0.357 *** (0.0000)	5208.634
KRW	0.485 *** (0.000)	0.765 *** (0.000)	0.323 *** (0.000)	6437.134
THB	0.468 *** (0.000)	0.758 *** (0.000)	0.325 *** (0.000)	6556.272
TRY	0.3457 *** (0.000)	0.583 *** (0.000)	0.236 *** (0.000)	6429.432
ZAR	0.543 *** (0.000)	0.858 *** (0.000)	0.421 *** (0.000)	5861.654

Levels of significance (*p*-value) are indicated between square brackets, where *** denotes significance at the 1% level and ** denotes significance at the 5% level.

3.2.3. Testing for Breaks-Points in the Series

We analyze the stability of series returns and volatility by referring to Bai and Perron (2003) and utilizing the absolute return as a proxy for volatility in order to detect change-points in the dependent structure (Bollerslev and Mikkelsen 1996; Andersen and Bollerslev 1997; Boutahar et al. 2008). The results (Table 6) demonstrate that there are two significant change-points. The sample is divided into three sub-samples at these transition points. The initial phase (pre-interruption 1) is marked by oil price stability (calm period). The next phase (between the two interruptions) has greater fluctuation than the first, while the third phase (post-interruption 2) has a higher level of volatility than the prior periods.

Table 6. Bai-Perron test for oil return volatility.

Sequential F-Statistic Determined Breaks: 2			
Break Test	**F-Statistic**	**Scaled F-Statistic**	**Critical Value ****
0 vs. 1 *	127.328	127.327	8.768
1 vs. 2 *	187.749	18.748	10.243
2 vs. 3	1.8110	1.810	11.234
Break dates:		Date	
1		18 September 2015	
2		10 July 2020	

* Significant at the 0.05 level. ** Bai-Perron critical values.

3.2.4. Dynamic Correlation and Conditional VaR Estimation Results

Estimation results for $cDCC$, copula, VaR, $CVaR$, and $\Delta CVaR$ are presented in Table 7.

According to the results, it can be noted that $5\% - VaR$ oil returns and $5\% - VaR$ of some exchange rates exhibit similar tendencies for most of the period. It is interesting to observe that VaR measures are powerless to establish that oil return upheaval implies these exchange rate defeats. Nevertheless, $cDCC$ and $CVaR$ measures can make it conceivable. As a consequence of the findings, we can see that the relationship among severe negative oil market returns and particular exchange rate series varies over time. Not only during the instability of the oil market (the third phase), but also during its stability, there is a strong positive link (the 1st phase).

It is observed from Table 7 that the absolute values for the VaR mean and for each emerging market nation indicate that the standard deviation of the oil price is larger than that of the exchange rate, implying that the crude oil price has a higher value-at-risk than the currency rate. It may be concluded that when the exchange rate varies little, the spillovers between the exchange rate and the oil price are minor, and vice versa. Furthermore, as seen in this table, the global economy has deteriorated as a consequence of the drop in crude oil prices in 2014–2016 and the coronavirus pandemic crisis, and the predicted damage of each country's exchange rate risk has increased, explicitly, the unconditional VaR rises. As a result of the effects of the crises, the information intensification consequence and investment sensitivity are exacerbated, and the risk spillover effect of a unique market or component is no longer dominant.

The results of the average conditional extreme losses ($CVaR$) show that the risk rises for all exchange rates, as soon as the conditional extreme losses are more important than the overall extreme losses implied by these exchange rates through the similar time period (VaR).

The results of $\Delta CVaR$ show that the exchange rate continued to be more exposed to oil market modifications through the last period, since $CVaR$ and $\Delta CVaR$ in this period are higher compared to the earlier period. By using $\Delta CVaR$, the same conclusions remain generally valid by means of the copula models. All the exchange rates had an absolute risk spillover on the international crude oil price over the study period, as exposed in

Table 7, and the variation trend of spillover strength illustrates a high degree of consistency. Particularly during the 2014–2016 international crude oil price drop, as well as other severe cases, the anticipated loss of crude oil price significantly augmented, and the risk of crude oil price developed by emerging market countries' exchange rates may be minor, following in an import decrease in the total risk spillover, which was not significant. For the oil-importing countries, spillover effects on the exchange rates are greater in most cases, and the situation during the pandemic is constant.

Table 7. VaR, $CVaR$, and $\Delta CVaR$ averages for series.

	Overall Period					**Pre-Break 1**				
	$c-DCC$	**Gumbel Copula** λ	VaR	$CVaR$	$\Delta CVaR$	$c-DCC$	**Gumbel Copula** λ	VaR	$CVaR$	$\Delta CVaR$
Exchange Rate of Oil-Exporting Countries										
BRL	0.7592	1.7435	−0.0043	−0.0052	−0.0044	0.0786	1.7123	−0.0036	−0.0051	−0.0028
CNY	0.8134	1.7895	−0.0042	−0.0057	−0.0034	0.7892	1.6785	−0.0046	−0.0063	−0.0036
MYR	0.8654	1.7623	−0.0038	−0.0052	−0.0033	0.9023	1.6983	−0.0037	−0.0048	−0.0304
MXN	0.8921	1.5674	−0.0035	−0.0046	−0.0031	0.8123	1.5321	−0.0030	−0.0043	−0.0026
PLN	0.7529	1.8764	−0.0038	−0.0054	−0.0028	0.7237	1.7956	−0.0035	−0.0049	−0.0024
RUB	0.7232	1.5679	−0.0034	−0.0048	−0.0026	0.6856	1.5347	−0.0034	−0.0047	−0.0023
Exchange Rate of Oil-Importing Countries										
INR	0.8023	1.6798	−0.0038	−0.0054	−0.0031	0.7345	1.6543	−0.0042	−0.0061	−0.0031
KRW	0.7903	1.8943	−0.0031	−0.0042	−0.0024	0.7673	1.8765	−0.0033	−0.0047	−0.0025
THB	0.7033	1.6453	−0.0049	−0.0068	−0.0035	0.7321	1.5895	−0.0043	−0.063	−0.0031
TRY	0.6782	1.5641	−0.0037	−0.0051	−0.0024	0.6432	1.5238	−0.0037	−0.0053	−0.0024
ZAR	0.6570	1.7644	−0.0045	−0.0063	−0.0031	0.5435	1.7254	−0.0039	−0.0055	−0.0020
	between Break 1 and Break 2					**Post-Break 2**				
	$c-DCC$	**Gumbel Copula** λ	VaR	$CVaR$	$\Delta CVaR$	$c-DCC$	**Gumbel Copula** λ	VaR	$CVaR$	$\Delta CVaR$
Exchange Rate of Oil-Exporting Countries										
BRL	0.7238	1.8453	−0.0037	−0.0054	−0.0028	0.8722	1.7345	−0.0046	−0.0063	−0.0039
CNY	0.7456	1.8466	−0.0034	−0.0046	−0.0025	0.8563	1.7578	−0.0056	−0.0077	−0.0049
MYR	0.8324	1.8467	−0.0032	−0.0046	−0.0027	0.9211	1.8021	−0.0054	−0.0074	−0.0049
MXN	0.8999	1.7687	−0.0031	−0.0042	−0.0028	0.8799	1.7276	−0.0043	−0.0054	−0.0040
PLN	0.7543	1.7643	−0.0035	−0.0049	−0.0026	07087	1.7257	−0.0037	−0.0053	−0.0026
RUB	0.7223	1.8245	−0.0031	−0.0047	−0.0024	0.8211	1.7665	−0.0038	−0.0052	−0.0031
Exchange Rate of Oil-Importing Countries										
INR	0.6754	1.7564	−0.0033	−0.0047	−0.0022	0.8765	1.6884	−0.0044	−0.0059	−0.0038
KRW	0.7321	1.9247	−0.0014	−0.0019	−0.0027	0.7845	1.8563	−0.0041	−0.0057	−0.0032
THB	0.6824	1.7453	−0.0047	−0.0065	−0.0029	0.6553	1.7285	−0.0064	−0.0089	−0.0042
TRY	0.6324	1.9345	−0.0032	−0.0045	−0.0019	0.7217	1.8452	−0.0042	−0.0059	−0.0029
ZAR	0.6578		−0.0044	−0.0063	−0.0031	0.6729		−0.0039	−0.0054	−0.0021

3.2.5. Consequences for Portfolio Designs and Hedging Strategies

The estimations concerning portfolio designs and hedging strategies (Table 8) demonstrate that the optimal portfolio weight for oil fluctuates significantly depending on the exchange rate. We observed that the proportions invested in exchange rate futures were more important than those invested in oil futures, indicating that those investors should maintain more exchange rate futures than oil futures. This finding persisted through the dot-com bubble burst, the pre-global financial crisis, the great Brent oil bust, and the coronavirus pandemic trigger. During a recovery period, results show that to hedge the risk, investors in exporting countries should retain more crude oil futures than the exchange rate. Furthermore, throughout different subperiods, the identical couples illustrated a variety of little and important weights, but with different sizes.

Table 8. The average values of the optimal weight, hedge ratio, and hedge effectiveness.

	Overall Period			**Pre-Break 1**		
	W_e	$B_{s/e}$	*HE*	W_e	$B_{s/e}$	*HE*
Exchange Rate of Oil-Exporting Countries						
BRL	0.156	0151	0.419	0.136	0.137	0.877
CNY	0.184	0.173	0.338	0.184	0.175	0.472
MYR	0.138	0.135	0.155	0.198	0.173	0.581
MXN	0.133	0.138	0.208	0.124	0.116	0.462
PLN	0.118	0.115	0.105	0.097	0.107	0.007
RUB	0.097	0.111	0.167	0.093	0.098	0.151
Exchange Rate of Oil-Importing Countries						
INR	0.156	0.148	0.463	0.132	0.135	0.183
KRW	0.119	0.116	0.372	0.115	0.105	0.087
THB	0.163	0.172	0.921	0.154	0.168	0.672
TRY	0.102	0.107	0.278	0.091	0.103	0.189
ZAR	0.122	0.131	0.403	0.067	0.099	0.052
	between Break 1 and Break 2			**Post-Break 2**		
	W_e	$B_{s/e}$	*HE*	W_e	$B_{s/e}$	*HE*
Exchange Rate of Oil-Exporting Countries						
BRL	0.145	0.149	0.082	0.186	0.171	0.632
CNY	0.185	0.161	0.146	0.187	0.169	0.129
MYR	0.185	0.136	0.144	0.163	0.145	0.274
MXN	0.181	0.154	0.578	0.217	0.154	0.294
PLN	0.172	0.157	0.099	0.195	0.107	0236
RUB	0.159	0.153	0.735	0.132	0.126	0.267
Exchange Rate of Oil-Importing Countries						
INR	0.163	0.121	0.159	0.152	0.138	0.216
KRW	0.137	0.123	0.535	0.100	0.101	0.079
THB	0.142	0.226	0.113	0.087	0.122	0.0143
TRY	0.104	0.111	0.001	0.112	0.119	0.0312
ZAR	0.139	0.176	0.602	0.106	0.117	0.112

The findings show that hedging a long position in any currency rate during a crisis is less expensive than during a quiet time. The ideal hedge-ratio values were low, indicating that the exchange rate investment risk can be mitigated by shorting oil futures markets. However, when we observe the hedge ratios over diverse subperiods, two separate sets of data are observed. Low hedge ratio values were in the first group, whereas high hedge ratio values were in the second. Lastly, we compared the hedging efficacy of a benchmark portfolio consisting just of precious metals to a hybrid portfolio consisting of two assets (i.e., exchange rates and crude oil futures). It has been discovered that including crude oil futures in the exchange rate improves hedging effectiveness for all pairings, regardless of current economic circumstances.

The average hedge ratios (Table 8) are low across the board, implying that hedging efficacy in the oil and exchange rate markets is relatively excellent. The values of the hedge effectiveness index HE, because of the lower values of hedged portfolio variance relative to unhedged portfolio variance, are positive for any exchange rate series. Lastly, during the coronavirus pandemic, all exchange rate-oil combinations had the highest hedging efficacy, suggesting that the oil market may be used as an exchange rate hedge in a portfolio.

4. Conclusions

From the financial crisis to the coronavirus epidemic, we address the topic of building a context for risk management and hedging strategies and the linkages between Brent crude oil and the national currency exchange rates of oil importing and exporting markets. The hedging and safe-haven features of Brent oil futures contracts are compared to those of emerging market nations' currency rates during different periods of calm and crisis, and the copula-$CVaR$ model is approved to investigate the bidirectional risk spillover effect among emerging market currency exchange rates and global crude oil prices. The risk spillovers are asymmetric over time.

Empirical findings indicate that there is considerable volatility spillover among the Brent oil market and the exchange rate markets, although the severity of the volatility interaction varies between exchange rate markets and periods. Furthermore, this paper focused on $\Delta CVaR$, and the findings differ based on the volatility of the Brent market returns for different periods and the currency rate for each country. Lastly, a technique for portfolio diversification methods is applied, which represent the greatest essential utilization for traders and market makers. The best weights and hedging ratios differed between times and currency rates, according to findings. This might be explained by the volatility of oil markets, which are more volatile than other developing market currency rates. Similarly, appropriate hedging ratios between the oil and exchange markets enable investors to efficiently hedge their oil risk by taking a short position in the exchange rate.

Our empirical results support the importance of some dates and events in the relationship between exchange and oil markets. This finding is in line with the results of (Kocoglu et al. 2023). Moreover, the spillover effect demonstrates diverse illustrations for the oil-exporting countries and oil-importing countries, which confirms the results of (Geng and Guo 2022). Likewise, findings indicate evidence of long-run dependence and asymmetry of bidirectional risk spillover between the crude oil price and exchange rate, and they indicate that the risk spillover intensity from the former to the latter is higher than that from the latter to the former, which is in line with the results of (Wang and Xu 2022). In particular, the risk of spillover is higher for the oil-exporting countries than for the oil-importing ones. We suppose that this can be explained by the fact that the persistence of exchange rate volatility during turbulent periods is aggravated by changes in international oil prices. Similarly, oil-exporting and oil-importing countries were affected by shocks. Nevertheless, during a turbulent period, differences exist within the countries. Which is in line with (Chatziantoniou et al. 2023).

Results show a negative dependence on oil returns and exchange rates. That is, the increase (or decrease) in oil prices implies an appreciation (or depreciation) in the exchange rate. We note that the oil price exchange rate dependence of oil exporters is higher than that of oil importers. Furthermore, the findings illustrate the existence of connectedness among oil price and exchange rate. Particularly exporting countries can be considered transducers of volatility, and importing countries can be considered receivers. However, this quality is varying with time, specifically during periods of turbulence. These results provide insights concerning the hedging strategies for institutional investors and policy makers in the context of oil and exchange markets.

Some potential shortcomings can be proposed. We can choose the onset of the global financial crisis and COVID-19 as breaks. This can help make a different comparison than that proposed in this study. Also, adding some figures can give a visual overview of some of the time series used in the empirical analysis. And to guarantee better implications for investors, policymakers, and respective exchange rate regulators from oil-trading countries, with further insights from the macro-economic perspective, we can distinguish between crises of economic origin and those of non-economic origin as we consider systemic and non-systemic crises. The case of COVID as a non-economic crisis is a good example here. As the exchange rate is one of the important transmission channels for the oil price shock to pass to the capital markets and to the real economy (Qiang et al. 2019), the question is whether monetary policy should take climate change into account for its transmission channels.

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Conflicts of Interest: The author declares no conflict of interest.

Note

[1] The results of the unit root tests are available upon request.

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