Journal of Infrastructure, Policy and Development 2024, 8(5), 4238.
https://doi.org/10.24294/jipd.v8i5.4238

Article

Hedging crude oil and currencies fluctuations

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CITATION

Boubaker H, Zorgati MBS. (2024). Hedging crude oil and currencies fluctuations. Journal of Infrastructure, Policy and Development. 8(5): 4238. https://doi.org/10.24294/jipd.v8i5.4238

ARTICLE INFO

Received: 15 January 2024
Accepted: 5 February 2024
Available online: 25 April 2024

Abstract: Relying on the D-Vine copula model, this paper delves into the hedging capabilities of Brent crude oil against the exchange rate of oil-exporting and oil-importing nations. The results affirm Brent crude oil's role as a safeguard and a refuge against the fluctuations of major currencies. Furthermore, we reaffirm that oil retains its robust hedging and safe-haven attributes during times of crisis, with currency co-movements across all countries exhibiting greater correlation than during the entire dataset. Additionally, our empirical findings highlight an unusually positive correlation between Brent crude oil and the Russian exchange rate during the Russia-Ukraine conflict, demonstrating that oil functions as a less effective hedge and a less dependable refuge for the Russian exchange rate in such geopolitical turbulence.

Keywords: crude oil; exchange rate; risk; hedging; drawable vine; crisis

1. Introduction

Hussain et al. (2023) affirm that throughout the last century, the global economy has witnessed multiple economic downturns that resulted in the collapse of various financial institutions. These events have underscored the robust connections among diverse categories of assets. With the objective of discovering improved strategies for asset allocation to effectively disperse risk during times of economic instability, it is natural to investigate the ever-evolving interconnections within financial markets to uncover patterns of transmission that can enhance comprehension of their attributes and dynamics. This is because, when information disseminates across different asset categories, both investors and policymakers have a vested interest in assessing the comprehensive consequences of their decisions, as financial and economic choices are more likely to exert inter-market impacts in particularly, the emergence of the COVID-19 pandemic in 2020 had a profound effect on the global economic landscape and various international markets. One noteworthy consequence has been the substantial volatility in oil prices directly attributable to the pandemic, a factor that significantly impacted financial markets, including the foreign exchange market.

In the context of finance, Martínez Raya et al. (2023) affirm that a collection of investments encompasses a range of underlying assets. Investors, whether individual or institutional, employ investment collections as a tactic to achieve diversification. The principal motivation behind this quest for diversification by investors is to mitigate the risk associated with holding volatile assets within the collection. By consequence, the task of crafting an investment portfolio and determining the allocation of assets has consistently presented a challenge to investors and fund managers, who are perpetually tasked with making informed decisions. The information concerning financial instruments serves as the input for this decision-making process, with the outcome being the distribution of an investor's wealth across the various underlying assets.

In the same analytical perspective, the macroeconomic consequences of fluctuations in commodity prices have consistently been a central focus in economic literature. More specifically, the prices of crude oil have traditionally served as a leading economic indicator. Further research has delved into the repercussions of oil price shocks on the labor market (Herrera et al., 2017) and real gross domestic product (Karaki, 2017). These discoveries provide motivation for investigating the impacts of energy price shocks on traded assets and exchange rates, aiming to gain deeper insights into the interplay between energy prices and economic dynamics.

The correlation between oil prices and macroeconomic and financial factors holds substantial significance for a variety of stakeholders. Zaremba et al. (2021) specify that among these factors, the foreign exchange rate stands out due to its potential to transmit shocks across multiple sectors. With the increasing integration of financial markets, it is imperative to pay special attention to understanding the mechanisms through which oil prices influence exchange rates. In the pre-financialization era of commodities, oil price shocks primarily impacted economies through traditional supply-side effects and current account balances. However, the process of financialization of commodities over the past few decades has, to some extent, altered this mechanism, particularly in the aftermath of the global financial crisis of 2008.

In this context, Beckmann et al. (2020) declare that the instability of commodity prices stands out as a primary catalyst for market volatility. In today's landscape, where investors and portfolio managers opt to incorporate commodities into their investment portfolios, we can readily discern the significance of commodities in the marketplace. Crude oil, being the most heavily traded commodity globally, exhibits the highest price fluctuation within commodity markets (Regnier, 2007). Oil prices play a pivotal role as the principal economic factor influencing the global economy, and they have undergone various fluctuations, rendering the oil market exceptionally volatile and laden with risk. Furthermore, the determination of crude oil prices hinges on global supply and demand dynamics. Given that the US dollar serves as the predominant currency for international crude oil transactions, the connection between commodities and foreign exchange rates has lately become a central focus of research. Lei et al. (2023) clarify that stakeholders in the petroleum industry, especially traders, producers, and consumers, are not only interested in fluctuations in oil prices but also in the correlation between energy commodity prices and currencies. This context of analysis holds significance for portfolio enhancement as investors pursue the best allocation of assets and the potential to yield exceptional returns during periods of turmoil. Recent research has sparked an escalating discussion regarding the influence of commodity price disruptions on foreign exchange markets.

In the context of volatility and according to Malik and Ewing (2009) oil price shocks do not explain the variation in exchange rate volatility. In fact, the volatility of commodity prices is one of the major drivers of volatility. The inclusion of commodities in investment portfolios by investors and portfolio managers today is a clear sign of the relevance of commodities in the market. According to Regnier (2007), crude oil, the most traded commodity in the world, represents the highest price volatility in the commodity markets. It provides a large part of the world's energy requirements and is an important part of the economy. Consequently, the volatility of oil prices has a significant impact on the economy.

The conflict between Ukraine and Russia has serious economic implications (Bourghelle et al. 2021). Furthermore, this crisis is happening during a particularly delicate time for the global economy as it strives to recover from the effects of the COVID-19 pandemic. Consequently, it may inhibit economic growth to some extent. The COVID-19 pandemic has had a negative impact on the world economy, particularly the oil industry.

It is worth noting that crude oil prices have been on the rise since the beginning of Russia-Ukraine conflict in late 2021 (Ma et al., 2021). In fact, Bagchi and Paul (2023) precise that Russia and Ukraine are the main suppliers of various agricultural products as well as crude oil It is possible that commodity prices may increase due to a number of factors, including fear of supply shortages, lack of physical infrastructure, and sanctions. The ongoing conflict between Russia and Ukraine is expected to have a major impact on the global economy in the form of higher commodity prices.

Within the same analysis framework, Isah and Ekeocha (2023) examine how fluctuations in oil prices influence the dynamics of exchange rate dynamics during periods of crisis. The authors hypothesize that the ability of oil prices to amplify exchange rate volatility during crises differs for economic and non-economic crises with different origins. The authors provide evidence that the divergent origins of different crises are important and can increase exchange rate volatility. And according to Bagchi and Paul (2023), the sustained increase in the tension between Russia and Ukraine led to the outbreak of the conflict, which constitutes the fundamental shock with a global impact in terms of long-term effect on the volatility of stock returns and currency exchange rates.

We will be looking at how fluctuations in crude oil prices influence currency markets, particularly during periods of economic and geopolitical crisis such as the conflict between Russia and Ukraine and the COVID-19 crisis, and how these fluctuations affect investors' asset allocation strategies to mitigate the risks? The rest of the document is structured as outlined below. Section 2 introduces the review of existing literature. Section 3 addresses the methodological framework, the data description and offers the initial examination. Section 4 examines results. Lastly, section 6 formulates the conclusion and proposes potential paths for future research.

2. Literature review

The relationship between oil prices and the exchange rate has been extensively research. It is widely accepted that crude oil plays an extremely important role in the economy due to its usage in production and consumption. On the other side, the exchange rate is considered a crucial indicator of a country's trade competitiveness. There is considerable interest in analyzing the dependence structure between the oil market and the exchange market, especially during periods of turbulence such as Covid 2019 and geopolitical conflicts, especially the Russian-Ukrainian one. In particularly, unexpected changes in oil prices can have an impact on a country's wealth through changes in the terms of trade and exchange rates. This is due to the transfer of income from oil imports to oil exports. It is important to note that the impact of oil price fluctuations on exchange rates is diffused through the channels of terms of trade and wealth effects. In this context, market participants are faced with the risk of price volatility and therefore need to protect their profits. Their primary objective is to ensure the lowest possible level of inflation. Consequently, it may be possible to use risk management approaches to limit the risk while optimizing profits to manage the price risk. Thus, the creation of a modelling of the most accurate risk measurement for the oil price has emerged as a key issue for better risk management in this context (Zorgati, 2023).

The variation of oil prices significantly impacts the implementation and analysis of a nation's macroeconomic strategy. A growing body of literature delves into the connection between the WTI rate and the currency exchange rate. Theoretically, the correlation between oil prices and exchange rates can be elucidated by the principle of price uniformity postulated by Golub (1983) and Krugman (1983). This theory posits that when oil prices surge, oil-exporting countries might encounter currency appreciation. However, when oil prices decline, these exporting nations could face currency depreciation, while the opposite holds true for oil-importing countries. In this context, Umar et al. (2023) examine the influence of oil price fluctuations on the foreign exchange rates of a distinct set of developed and emerging economies. Their findings reveal that demand and risk fluctuations are the primary factors contributing to the between oil shocks and exchange rates interconnections. In particularly they observe that the Singaporean dollar and the Malaysian Ringgit play pivotal roles in transmitting shocks, while the Chinese yuan and the Japanese yen have limited influence despite the larger size of their respective economies. Beckmann and Czudaj (2022) validated transmission channels for the interplay between oil prices and exchange rates as the terms of trade channel; the wealth and portfolio channel; the denomination channel and the expectation channel.

In their analysis, Cunado and Gracia (2005) examine the correlation between oil prices and the macroeconomy across different time periods and regions. Their findings suggest that while oil shocks do have a noticeable impact on economic activity and consumer price indices in the short term, this impact is limited. This is especially true when considering local currencies. According to Cunado and Gracia (2003), oil prices have permanent effects on inflation and asymmetrical short-term effects on output growth in several European countries between 1960 and 1999. In the same vein, Cunado and Gracia (2014) examine the impact of oil shocks on European stock market returns. According to the study, it appears that oil supply shocks may have a notable and adverse effect on the performance of the European stock market.

A comprehensive examination of the existing theoretical and empirical research concerning the connection between oil prices and currency exchange rates is conducted by Beckmann et al. (2020). They discovered that the outcomes observed varied based on the sample used, the choice of countries, and the practical methodologies employed. They reached the conclusion that exchange rates and oil prices often exhibit robust long-term correlations. In the short term, either exchange rates or oil prices can serve as a significant predictor of the other variable, but their impacts are subject to considerable time variations. Consequently, it is imperative to analyze the relationship between these two factors employing a time-varying approach.

They confirm that the link between oil prices and exchange rates has rekindled interest among academics, policymakers, and investors. This relationship garnered heightened attention during the Global Financial Crisis period. Since the year 2000, oil prices have experienced a substantial upward trajectory, particularly in the aftermath of the crisis period. The price of crude oil exerts a profound influence on both the real economy and financial markets. Indeed, the crude oil price stands as a critical determinant capable of elucidating fluctuations in the exchange rate.

Several studies have been conducted on the relation between oil prices and exchange rates. Brander et al. (1983) and Golub (1983) were among the first to develop models describing this link between oil prices and the dollar exchange rate. They found that the exchange rates of oil exporting countries appreciate when the oil price rises and it depreciates the exchange rates of oil importing countries, that's why the oil will be sold at a high price and oil importing countries have to pay more and then the value of oil exporting countries' currencies will be appreciated against US dollar.

Most studies in this literature have found a positive correlation between oil prices and the value of the dollar. This implies that an increase in the price of oil is accompanied by an appreciation of the dollar. Amano and Van Norden (1998). Explored the causality of the long-run relationship between oil prices and exchange rates in Germany, Japan and the United States by using Granger causality tests and cointegration tests, they established that the real oil price is the cause of the long-run evolution of real exchange rates in the post-Bretton Woods period.

The co-movement of oil prices and currency exchange rates through the utilization of two indicators of interrelation: correlations and copulas are explored by Roboredo (2012). The study reports two primary discoveries regarding crude oil prices and various currencies: The interdependence among oil prices and exchange rates is typically feeble, although it notably escalated following the global financial crisis. Furthermore, there is no excessive market interdependence between oil prices and currency exchange rates.

The extent of time varying connection and transmission of influence among commodities and the foreign exchange rates of Sub-Saharan African nations is assessed by Opoku et al. (2023). They employ spillover indicator to depict the evolving connections in both the time and frequency dimensions. Their analysis demonstrates that the correlation between commodity returns and SSA exchange rates is subject to variations over time and across different frequencies, with stronger correlations observed at higher frequencies. They observe that only crude oil serves as the dominant initiator of spillover effects. These findings reveal substantial transmissions of influence between commodities and exchange rates during economic turbulence, indicating the presence of contagion among the markets.

The cross-spectral coherence and correlation between the monthly returns of WTI crude oil prices and the exchange rate of the Thai Baht against the US Dollar spanning from 1986 to 2019 is examined by Kyophilavong et al. (2023). They employ a quantile-based cross-spectral methodology and a time-frequency wavelets as estimation tools. Findings from the quantile coherency analysis reveal adverse spillover impacts of oil prices on Thai exchange rates in the short, intermediate, and long terms, indicating that the oil market presents systemic risk to the foreign exchange market in Thailand across various time horizons. Wavelet analysis highlights an absence of co-movements at high frequencies, representing the short term. However, additional outcomes indicate positive and negative correlations between oil prices and the Thailand-US exchange rate across different time periods and frequency ranges, with the effects being more pronounced during periods of heightened volatility.

The predictive power of extreme oil market risk, both within the sample and out of it, on the extreme risk associated with U.S. Dollar exchange rates (USD/CAD, USD/GBP, and USD/JPY) is analyzed by Salisu et al. (2022). They utilize conditional autoregressive value at risk to estimate extreme risks. Subsequently, they formulate a predictive model by selecting the most suitable extreme risks, and then assess the predictive capability of oil market risk for both in-sample and out-of-sample forecasts. Their findings reveal a positive correlation between oil market risk and USD risk for USD/CAD and USD/GBP. Incorporating the dynamics of oil market risk into the predictive model for USD exchange rate risks enhances both in-sample and out-of-sample forecasts.

Furthermore, Mensi et al. (2017) investigate the interconnections in the short and medium term between oil and currency markets. They employ the variational mode decomposition, in combination with an array of time-invariant and time-varying copula functions, both symmetric and asymmetric. Additionally, they evaluate the negative and positive short- and medium-term risk transmissions from oil to U.S. exchange rate returns and vice versa, by calculating conditional Value-at-Risk risk metrics. Their results from the copula analysis reveal compelling indications of time-varying and substantial interdependence between oil returns and the foreign exchange markets. Conversely, they find moderate and fairly limited dynamic interrelation between oil and currencies that serve as net receivers, regardless of the timeframes. Moreover, they confirm the presence of asymmetric systemic risk transfers, both upward and downward, between oil and currencies, within short- and medium-term horizons. Lastly, they note that risk transmissions exhibit temporal and investment horizon asymmetries.

Likewise, Sun et al. (2022) examine whether the connections between China’s foreign exchange rate, domestic raw petroleum cost, and the global crude oil cost exhibit a shift in behavior before and after the introduction of China’s crude oil futures by the Shanghai International Energy Exchange (INE) by employing the MS-VAR model. Their findings reveal that, despite the profound influence of the international crude oil market on China’s oil prices, its influence on the global crude oil price is relatively feeble. Following the inauguration of INE crude oil futures within the new framework, the fluctuations in the USD to RMB exchange rate have displayed a notably positive impact on China’s crude oil prices. Also results show that the initiation of Brent or Oman crude oil futures does not induce the same effects as the commencement of INE crude oil futures. This suggests that the favorable impact of the USD/CNY exchange rate on INE crude oil futures prices can potentially transmit to China’s spot crude oil market.

Notwithstanding, Isah and Ekeocha (2023) affirm that oil prices have increasingly been recognized as a pivotal factor in the fluctuations of exchange rates. Consequently, they explore the impact of oil price fluctuations on exchange rate dynamics during crisis scenarios. They postulated that the potential of oil prices to amplify exchange rate volatility during crises differs between economic and non-economic crises with distinct origins. Accordingly, they categorized the crisis dataset into two subsets: the significant recession stemming from the 2007 global financial crisis and the extensive lockdown resulting from the COVID-19 outbreaks. They employed the GARCH model and its various extensions and observed three key outcomes. Firstly, they demonstrate that the diverse origins of economic and non-economic crises have a significant impact on the degree to which they intensify exchange rate volatility. Secondly, the duration of exchange rate volatility during the COVID-19 crisis is exacerbated by fluctuations in international oil prices. Lastly, their discovery of varying patterns of persistent exchange rate volatility across different sets of turbulent periods furnishes investors with evidence-based insights to refrain from applying a one-size-fits-all portfolio selection strategy in the midst of economic crises stemming from different sources.

Within the same analytical framework, Zeng et al. (2022) employ the approach of multivariate GARCH models and Vine-Copula-CoVaR to examine the associations between interdependence, systemic risk transmission, and volatility transmission involving the USD/CNY exchange rate and the returns on WTI crude oil futures. They observe a more intricate interdependence of the USD/CNY exchange rate with stock markets and WTI crude oil prices. All of them exhibit negative risk transmissions between the paired markets, with WTI displaying the most significant risk transmission. Nevertheless, the magnitude of systemic risk transmission varies across the markets. Also results confirm notable mean transmission from the Chinese stock market and the USD/CNY exchange rate to the WTI crude oil price.

To add to that, Wang et al. (2022) introduce a dynamic factor model to accurately depict the evolving interdependence and risk transfer between the returns on crude oil and exchange rates in oil-trading countries during the period 2000–2020, based on common factors. First, they identify the shared factors linked to returns of crude oil prices and exchange rates across 14 representative oil-trading nations. Next, they employ the AR-GARCH model to separate the respective unique factors and perform a comparative analysis of the conditional dynamic interdependence between the returns on crude oil and exchange rates for oil importers and exporters. Ultimately, they amalgamate the dynamic factor copula model with the CoVaR method to gauge the conditional risk transmission effect between crude oil and exchange rate markets. Their findings confirm that the factor copula model can more precisely capture the evolving relationship between crude oil and exchange rate markets compared to the conventional Copula-GARCH model. Specifically, the unique factors related to each return series still exert a notable influence on the interdependence between the returns on crude oil and exchange rates for oil importers, while the common factors have played a crucial role in the correlation between exchange rates of oil-exporting nations and crude oil prices. Lastly, the crude oil market has exhibited a relative risk premium compared to the exchange rate markets of oil-trading countries. Nevertheless, results show that there is virtually no conditional risk transmission from the corresponding exchange rates to crude oil prices.

Equally important, Sokhanvar and Bouri (2023) assert that the conflict in Ukraine and the imposition of fresh sanctions on Russia have had repercussions on commodity prices, leading to significant movements in currency exchange markets. They explore the influence of commodity price fluctuations associated with the Ukraine conflict on three currencies: the Canadian dollar, the euro, and the Japanese yen. By employing four-hour price data for three commodities (wheat, crude oil, and natural gas) and two currency exchange rates (EUR/CAD and CAD/JPY) spanning from 1 February to 30 April 2022, their analysis, based on the quantile autoregressive distributed lag (ARDL) model, indicates a lasting correlation between elevated commodity prices and the strengthening of the Canadian dollar against both the euro and the yen. Moreover, the dynamic ARDL model simulations reveal a positive effect of commodity price shocks on the value of the Canadian dollar relative to the euro and the yen, underscoring the resilience of our findings. Oil price shocks exhibit a nearly identical impact on the depreciation of the euro and the yen. Alongside higher oil prices, the depreciation of the euro is driven by elevated gas prices, while increased wheat prices play a pivotal role in the depreciation of the yen.

Correspondingly, Shang and Hamori (2023) affirm that the connection between exchange rates and crude oil prices is of substantial significance when seeking to grasp the dynamics of oil markets and their ramifications for various economies. By employing the time-varying copula they explore the links between foreign currency exchange rates (FX) and West Texas Intermediate (WTI) crude oil prices, with a particular emphasis on varying tail association and fluctuating linear connection. Results ascertained that the tail association between foreign currency exchange rates (FX) and WTI crude oil prices is more pronounced for nations that export oil in comparison to those that import it. Additionally, the impact of the COVID-19 pandemic has further intensified the tail association for oil-exporting nations, while concurrently augmenting the correlation between FXs and WTI for oil-importing nations. However, the 2022 Russian–Ukrainian conflict has exerted a notable diminishing effect on both the tail association and linear correlation of FXs and WTI, reaching or even surpassing levels akin to those experienced during the 2008 financial crisis

3. Methodology, data description and initial examination

3.1. Vine copula

In recent years, copulas have been used in several fields such as econometric modeling and quantitative risk management due to their ability to capture the nature of multivariate data distributions and their dependencies. It is a relatively old statistical tool introduced by Sklar (1959) updated by Genest et al. (1986) forming a multivariate distribution function. It is based on Sklar's theorem.

A d-dimensional copula is the distribution function of a random vector U whose components are uniformly distributed. That is:

For every random vector $u = (u_1, \ldots, u_d) \in (0,1)^d$,

$$C(U_1 \leq u_1, \ldots, U_d) = P(U_1 \leq u_1, \ldots, U_d \leq u_d \tag{1}$$

For a random vector $X = (X_1, X_2, \ldots, X_d) \in \mathbb{R}^d$ with distribution function $F(x_1, \ldots, x_d) = P(X_1 \leq x_1, \ldots, X_d \leq x_d)$ and continuous marginal distribution function $F_i(x) = P(X_d \leq x)$ for all *i* = 1, …, *d*.

There exists a unique d-dimensional copula function $\mathrm{C} \in [0,1]^d$ such that

$$F(x_1, x_2, \dots, x_d) = C(F_1(x_1), F_2(x_2), \dots F_d(x_d)) \quad (2)$$

where $(x_1, x_2, \dots, x_d) \in \mathbb{R}^d$.

From the previous equation, we obtain the copula formula as follow:

$$C(u_1, \dots, u_d) = F\left(F_1^{-1}(u_1), \dots, F_d^{-1}(u_d)\right) \quad (3)$$

where we denote F_i^{-1}: The inverse marginal distribution functions and $u_i = F_i(x_i)$ for all $i = 1, \dots, d$.

Multivariate copulas are implemented for dimensions $d \geqslant 3$ and are restricted to non-tail correlated Gaussian and symmetric Student-t in more complex copulas and asymmetric tail-dependent functions. A d-dimensional distribution is decomposed from the density into a series of connected bivariate copula trees constructed as blocks called regular vines (R-vines).

Vines are used to designate the graphical representation of the pair copula constructions (PCC) proposed by Bedford et al., (2001, 2002). Aas et al. (2009) have showed that R-Vines is decomposed in two: C-vines (Canonical Vine) and D-vines (Drawable Vine). Dependence modeling using vine copulas offers a greater flexibility and permits the modeling of complex dependency patterns for high-dimensional distributions.

V is a vine on d variables if:

$$V = (T_1, \dots, T_{d-1})$$

T_1 is a tree with nodes $N(T_1) = \{1, 2, \dots, d\}$ and edges $E(T_1)$.

For $\ell > 1$,T_ℓ is a tree with nodes $N(T_\ell) = E(T_{\ell-1})$.

For $i = 2, \dots, d-1$, T_i is a tree with nodes $N_i = E_{i-1}$ and a set of edges E_i.

V is called a regular vine on d elements if we add a third condition to the two previous ones:

For $i = 2, \dots, d-1$, if $a = \{a_1, a_2\}$ and $b = \{b_1, b_2\}$ are nodes of T_i linked by an edge, then exactly one of the a_i equals one of the b_i.

3.2. Drawable vine copula

The d-dimensional density of the D-Vine is given by:

$$f_D(x_1, \dots, x_d) = \prod_{k=1}^{d} f(x_k) \prod_{\mathrm{j}=1}^{\mathrm{d}-1} \prod_{i=1}^{d-j} C_{i,i+j|1+i,\dots,i+j-1} \left[F\left(x_i \middle| x_{1+i}, \dots, x_{i+j-1}\right), F\left(x_{j+i} \middle| x_{1+i}, \dots, x_{i+j-1}\right)\right] \quad (4)$$

where $C_{i,i+j|1+i,\dots,i+j-1}$ is the bivariate copula density.

The example of 5-dimensional D-vine density is given by:

$$\begin{aligned} f(x\_1, x\_2, x\_3, x\_4, x\_5) \\ &= c\_1{,}2(F\_1(x\_1), F\_2(x\_2)) \times \_2{,}3(F\_2(x\_2), F\_3(x\_3)) \times c\_3{,}4(F\_3(x\_3), F\_4(x\_4) \\ &\times c\_4{,}5(F\_4(x\_4), F\_5(x\_5)) \times c\_(1{,}3|2)(F\_(1|2)(x\_1|x\_2), F\_(3|2)(x\_3|x\_2)) \\ &\times c\_(2{,}4|3)(F\_(2|3)(x\_2|x\_3), F\_(4|3)(x\_4|x\_3)) \\ &\times c\_(3{,}5|4)(F\_(3|4)(x\_3|x\_4), F\_(5|4)(x\_5|x\_4)) \\ &\times c\_(1{,}4|2{,}3)(F\_(1|2{,}3)(x\_1 \mid x\_2, x\_3), F\_(4|2{,}3)(x\_4 \mid x\_2, x\_3)) \\ &\times c\_(2{,}5|3{,}4)(F\_(2|3{,}4)(x\_2 \mid x\_3, x\_4), F\_(5|3{,}4)(x\_5 \mid x\_3, x\_4))) \\ \times c_{1,5|2,3,4} &\left(F_{1|2,3,4}(x_1|x_2, x_3, x_4), F_{5|2,3,4}(x_5|x_2, x_3, x_4)\right) \times f_1(x_1) \times f_2(x_2) \times f_3(x_3) \times f_4(x_4) \times f_5(x_5) \end{aligned} \quad (5)$$

Aas et al. (2009) suggested two inference algorithms for estimation of D-vine log-likelihoods. D-vine copula models are usually fitted by iteratively proceeding tree by tree, thus only needing bivariate estimation for each single pair-copula term (Czado et al. 2012).

Therefore, estimation of the parameter(s) of each pair copula can be done by Kendall's τ inversion or maximum likelihood estimation.

Czado et al. (2012) suggested a sequence estimation procedure for vine ligatures.

First, the parameters of the unconditional pair copulas in the first tree are determined, then the parameter used to determine the conditional pair copulas in the second tree is estimated, and also used to estimate the two conditional variable pair copulas in the third tree. The method should be repeated until all the parameters of the paired copulas have been determined.

As a last step, these successive estimates are used as a starting point to calculate the maximum likelihood estimate of the vine copula.

Assume that we observe d variables at T time points.

Let $x_i = (x_{i,1}, \ldots, x_{i,T})$;$i = 1, \ldots, d$

The log-likelihood for D-vine is given as:

$$lnf(x) = \sum_{j=1}^{d-1} \sum_{i=1}^{d-j} \sum_{t=1}^{T} ln\left(c_{i,j+i|1,\ldots,(i+j-1)}\left(F\left(x_{i,t}\middle|x_{i+1,t}, \ldots, x_{i+j-1,t}\right), F\left(x_{i+j,t}\middle|x_{i+1,t}, \ldots, x_{i+j-1,t}\right)\right)\right) \tag{6}$$

$\theta_{j,i}$ is the set of parameters of the copula density $c_{i,j+i|1,\ldots,(i+j-1)}$.

The conditional distribution functions are computed using (Joe, 1997):

$$F(x|v) = \frac{\partial c_{x,v_j|v_{-j}}(F(x|v_{-j}), F(v_j|v_{-j}))}{\partial F(v_j|v_{-j})} \tag{7}$$

v is a d-dimensional vector;

v_j is an arbitrarily select component of v;

v_{-j} signifies the v-vector excluding the component v_j.

If v is univariate; x and v are uniformly distributed on [0, 1], then $F(x|v) = \frac{\partial c_{x,v}(x,v,\theta)}{\partial v}$, where θ is the set of copula parameters.

For the D-vine, $F(X_j|X_1, X_2, \ldots, X_{j-1})$ is given by:

$$\frac{\partial c_{j,1|2,\ldots,j-1}(F(x_j|x_2, \ldots, x_{j-1}), F(x_1|x_2, \ldots, x_{j-1})}{\partial F(x_1|x_2, \ldots, x_{j-1})} \tag{8}$$

Modeling all returns and their volatilities involves of two steps:

The first step involves the description of the ARMA(1,1) model for mean returns. The second step is the description of the GARCH(p,q) models for conditional volatility.

To model the conditional mean, we conducted over alternative ARMA(p,q) models by varying p and q parameters from 1 to 3. The optimum model was selected using BIC and AIC.

The dynamics of volatility in the presence of asymmetry effects for all variables are explored using asymmetric GARCH models, such as GARCH(1,1), EGARCH(1,1), GJR-GARCH(1,1), and APARCH(1,1).

3.3. Data description

In this section, we delineate the dataset employed in our empirical examination, encompassing the chosen countries, the timeframe under consideration, the variables, and the origins from which the data was procured. All variables start at 02/01/2015 and end in 05/12/2022. Countries are selected in terms of oil production.

- Russia (RUB);
- United European (EUR);
- Canada (CAD);
- China (CNY).

We will focus on two periods of crisis: The COVID-19 pandemic (from December 2019 to April 2021) and the invasion of Russia-Ukraine (from February 2022 to October 2022).

For Exchange rates: we defined exchange rates as the amount of local currency to one US Dollar. The data for each exchange rate was taken from DATASTREAM. For: Crude oil: The real crude oil prices are defined as the spot price per barrel denominated in US dollar: BRENT. The data was taken from United States Energy Information Administration (EIA).

Table 1 offers the summary of the data set and **Figure 1** presents a description of the daily prices of series.

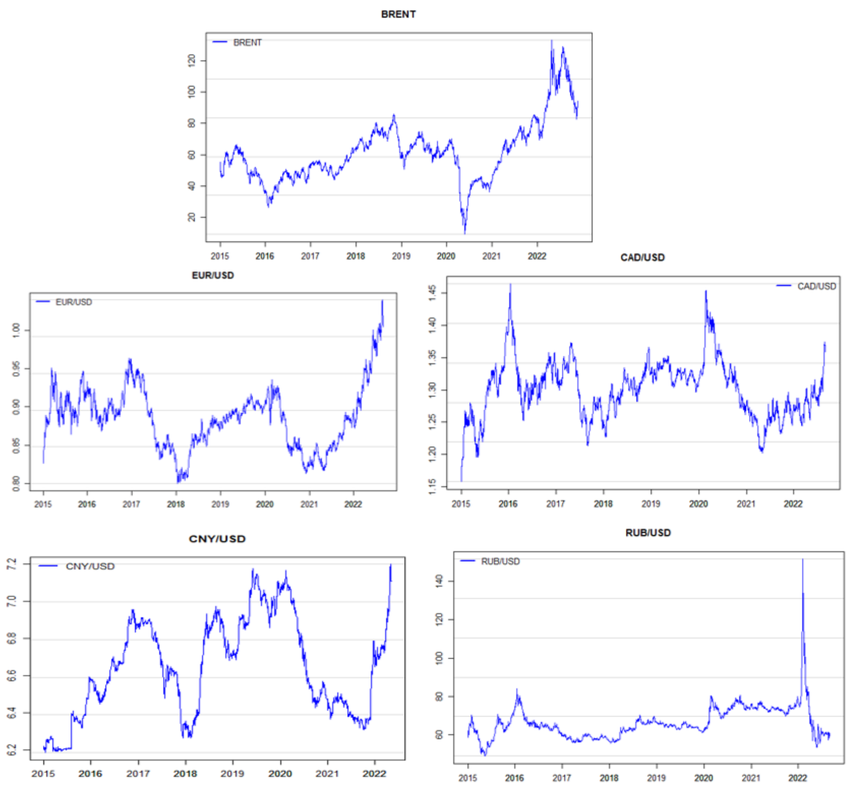

Figure 1. Daily prices of series.

For the initial observation, the chart indicates that in early 2016, the per-barrel price of Brent plummeted to $26, followed by a gradual increase to reach $80 per barrel by the close of 2018. In 2019, a slight decline to $50 per barrel is evident, attributed to the attack on critical energy facilities in Saudi Arabia. Towards the end of 2019 and into 2020, a historic plunge in barrel prices ($9) is observed due to the COVID-19 pandemic. The enforced lockdown led to a reduction in consumption, resulting in a negative demand shock. Simultaneously, the lockdown curtailed the overall production of countries, constituting a negative supply shock. In 2022, the price of Brent witnessed a substantial surge, reaching $127 by the end of March 2022, propelled by the Ukraine-Russia invasion. Regarding the currency exchange rates, it is observed that the four charts exhibit similarities. Specifically, each graph displays three peaks: One in 2017 for importing nations, one in 2016 for exporting nations, and two additional peaks in 2020 due to the COVID-19 pandemic and in 2022 resulting from the Ukraine-Russia war. All fluctuations exhibit distinct upward and downward trends, with a downward slope indicating an overall average trend. Consequently, they do not revolve around a consistent mean. Additionally, the varying volatility suggests that the variance is not uniform. As all series exhibit non-stationarity, it is customary in time series analysis to model correlated changes in prices, particularly in log return series (refer to **Figure 2**).

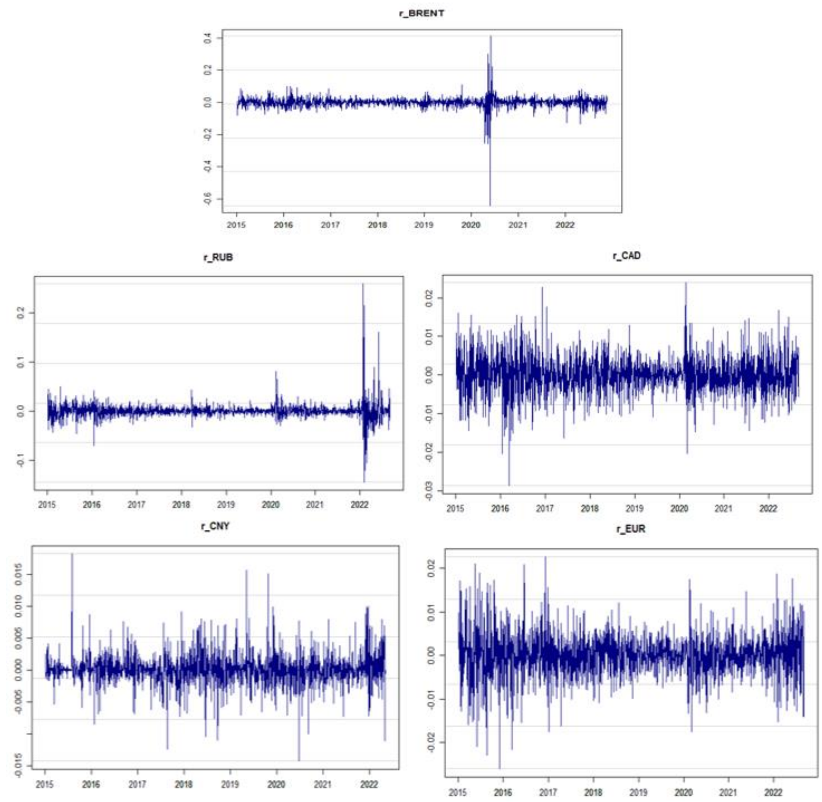

Figure 2. Returns series.

Visually, the upward trend appears to have been nullified, and the series mean aligns with a line parallel to the x-axis. This affirms the stationarity of the series, an aspect we will confirm through a stationarity test, as we will elaborate on later. With the daily spot prices of the database transformed into daily returns, conducting statistical analysis on the series becomes more straightforward. Significant deviations in the BRENT plot during the COVID-19 pandemic in 2020 are observable. Concerning the other plots, notable high deviations occurred in 2016, 2020, and 2022.

The outcomes indicate that all the statistical tests for our variables significantly exceed the critical value at the 5% significance level (p-value < 1%). This results in rejecting the null hypothesis of normality, implying that the distributions of the daily return series deviate from the normal distribution.

The standard deviation serves as a statistical gauge of market volatility, quantifying the extent to which prices diverge from the average price. In instances where prices trade within a narrow range, the standard deviation yields a low value, indicating diminished volatility. **Table 1** illustrates that the exchange rate CNY/USD exhibits the lowest standard deviation, while BRENT prices display the highest standard deviation, signifying that CNY/USD experiences the least volatility and BRENT encounters the most volatility. Essentially, a small standard deviation implies that the values in a statistical data set closely align with the dataset's mean. It is noteworthy that all deviations are minimal, affirming that all series orbit around the mean.

Table 1. Descriptive statistics of returns series.

	Mean	Maximum	Minimum	Std.Deviation	Skewness	Kurtosis	Jarque-Bera
Brent	0.0002699	0.41202	−0.643699	0.033953	−2.766159	88.2145	599777
EUR	0.0001014	0.02259	−0.026006	0.004985	−0.026543	5.24938	426.94
CAD	8.255793×10^{-5}	0.02392	−0.028697	0.004875	−0.004375	4.93313	315.16
RUB	6.544084×10^{-6}	0.25884	−0.145388	0.015695	3.590823	74.0029	429510
CNY	7.026998×10^{-5}	0.01816	−0.014285	0.002465	0.458218	8.82791	2811.9

In this context, skewness is employed to assess the extent of asymmetry in a distribution. which is considered left-skewed if there is a tail on the left side, while it is deemed right-skewed if the tail is on the right side. Symmetry is asserted when the distribution is balanced on both sides. Skewness values can span from negative infinity to positive infinity. In our context, as delineated in **Table 1**, negative skewness values for Brent, EUR/USD, and CAD/USD signify left-sided tails in the distribution, indicating a prevalence of negative values. Conversely, positive skewness values for RUB/USD and CNY/USD denote right-sided tails in the distribution, favoring positive values. The kurtosis level surpasses 3 in all variables, indicating a distribution with more pronounced peaks than the normal distribution. This suggests that substantial fluctuations in daily prices are more frequent than predicted by the normal distribution, with fatter tails. Consequently, the findings challenge the assumption of normally distributed returns. To confirm the stationarity of our returns series, we employ the Augmented Dickey-Fuller Test (ADF) for unit root testing and the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) stationarity test. The outcomes reveal that the p-values for all variables are below 5%, indicating the rejection of the null hypothesis of non-stationarity. Consequently, all series are deemed stationary.

A test for normality assesses whether a dataset adheres to a population with a normal distribution. However, it's crucial to emphasize that strict adherence to a normal distribution is not mandatory. Therefore, a diligent researcher should confirm the actual normality of the data or explore alternative distributions that might better model them. Additionally, it's noteworthy that the kurtosis and skewness coefficients (refer to **Table 1**) serve as indicators of normality. As all variables exhibit non-zero skewness and kurtosis values exceeding 3, we deduce that none of the variables follow a normal distribution. Various methods, including histograms, QQ-plots, and the Jarque Bera Test, are employed to scrutinize the normality of the data.

Modeling all returns and their volatilities consists of two steps:

The first step involves the specification of the ARMA(1,1) model for mean returns. The second step is the specification of the GARCH(p,q) models for conditional volatility.

Our method for modeling the conditional mean is to search over alternative ARMA(p,q) models by changing p and q parameters from 1 to 3, and identifying the optimum model using the BIC and AIC (refer to **Table 2**).

Table 2. Information criteria for possible ARMA process.

	BRENT		EUR/USD		CAD/USD		RUB/USD		CNY/USD	
	BIC	**AIC**	**BIC**	**AIC**	**BIC**	**AIC**	**BIC**	**AIC**	**BIC**	**AIC**
ARMA(1,1)	−7728.5	−7750.8	−15687.4	−15715.1	−15771.6	−15799.1	−11046.8	−11069.2	−17758.2	−17780.5
ARMA(1,2)	−7728.2	−7756.2	−15681.8	−15709.9	−15771.3	−15799.3	−11041.75	−11069.81	−17766	−17793.8
ARMA(1,3)	−7725.4	−7758.9	−15679.6	−15713.3	−15764.6	−15798.3	−11040.64	−11074.32	−17759.09	−17792.51
ARMA(2,1)	−7729.1	−7757.1	−15683.8	−15711.9	−15772.4	−15800.5	−11042.9	−11070.96	−17766.17	−17794.02
ARMA(2,2)	−7744.1	−7777.6	−15676.2	−15709.9	−15772.7	−15806.4	−11068.41	−11102.09	−17758.9	−17792.32
ARMA(2,3)	−7736.9	−7776.1	−15672.2	−15711.5	−15765.2	−15804.5	−11076.87	−11116.16	−17751.36	−17790.35
ARMA(3,1)	−7725.6	−7759.1	−15679.5	−15713.2	−15765.2	−15798.9	−11039.89	−11073.57	−17759.09	−17792.51
ARMA(3,2)	−7736.8	−7776.1	−15672.1	−15711.4	−15765.2	−15804.5	−11077.54	−11116.83	−17751.49	−17790.48
ARMA(3,3)	−7729.3	−7774.1	−15670.1	−15709.8	−15758.3	−15803.2	−11070.27	−11115.18	−17744	−17788.56

The model, which has the deepest BIC and AIC, will be selected. For the daily returns of the Brent (refer to **Table 3**), the best model is ARMA(2,2) , for EUR/USD (refer to **Table 4**), the best model is ARMA(1,1), for CAD/USD the best model is ARMA(2,2) (refer to **Table 5**), for RUB/USD the best model is ARMA(3,2) (refer to **Table 6**), for CNY/USD, the best model is ARMA(2,1) (refer to **Table 7**).

For the conditional variance, we use to discover the dynamics of volatility in presence of asymmetry effects for all our variables. We study asymmetric GARCH models: GARCH(1,1), EGARCH(1,1), GJR-GARCH(1,1) and APARCH(1,1).

Table 3. The selection of model by information criteria: BRENT.

	GARCH	EGARCH	GJR-GARCH	APARCH
AIC	−4.6168	−4.6368	−4.7032	−4.6388
BIC	−4.6055	−4.6227	−4.6862	−4.6219
Log Likelihood (LL)	4560.816	4581.534	4648.079	4584.539

Table 4. The selection of model by information criteria: EUR/USD.

	GARCH	EGARCH	GJR-GARCH	APARCH
AIC	−7.9199	−7.9111	−7.9532	−7.9019
BIC	−7.9089	−7.8973	−7.9365	−7.8852
Log Likelihood (LL)	8018.984	8011.079	8054.603	8002.703

Table 5. The selection of model by information criteria: CAD/USD.

	GARCH	EGARCH	GJR-GARCH	APARCH
AIC	−7.8995	−7.9002	−7.9430	−7.8893
BIC	−7.8884	−7.8863	−7.9263	−7.8727
Log Likelihood (LL)	7998.255	8000.013	8044.296	7990.003

Table 6. The selection of model by information criteria: RUB/USD.

	GARCH	EGARCH	GJR-GARCH	APARCH
AIC	−6.4670	−6.4783	−6.6014	−6.4851
BIC	−6.4559	−6.4644	−6.5848	−6.4685
Log Likelihood (LL)	6548.613	6561.036	6686.613	6568.965

Table 7. The selection of model by information criteria: CNY/USD.

	GARCH	EGARCH	GJR-GARCH	APARCH
AIC	−9.1555	−9.2212	−9.5419	−9.2139
BIC	−9.1440	−9.2068	−9.5247	−9.1966
Log Likelihood (LL)	8880.233	8944.922	9256.914	8938.83

After estimating the different models, we conclude that the best models to be applied are the ARMA(2,2)GJR-GARCH(1,1) for the BRENT, ARMA(1,1)GJR-GARCH(1,1) for EUR/USD, ARMA(2,2)GJR-GARCH(1,1) for CAD/USD, ARMA(3,2)GJR-GARCH(1,1) for RUB/USD and ARMA(2,1)GJR-GARCH(1,1) for CNY/USD.

Table 8 shows that the parameter α varies between 0.05 and 0.1, it is low and significant. The GARCH persistence parameter β is higher than 0.85 for all series which means that it is significant and approves the higher volatility. Moreover, ARCH(1) coefficients are low and significant. The high α which is often related with a low β produces GARCH volatilities with a higher volatility of volatility. As a consequence, all series are defined by significant GARCH effects.

Table 8. Estimation results.

	BRENT	EUR/USD	CAD/USD	RUB/USD	CNY/USD
C	0.0021602*	0.00016913*	3.5869×10^{-6}	−0.0001359	-3.2613×10^{-6}
AR(1)	−0.81779**	−0.66875**	0.13143***	−0.35309**	−0.67787**
AR(2)	−0.15018*	-	0.78877*	−0.11641*	−0.050868*
AR(3)	-	-	-	−0.042599	-
MA(1)	0.8369*	0.70476*	−0.1237**	0.37648*	0.61409
MA(2)	0.14937*	-	−0.80326**	0.10725*	-
Constant ω	2.4888×10^{-5}*	2×10^{-7}	2×10^{-7}**	1.5584×10^{-6}	2×10^{-7}
GARH(1)(β)	0.85718***	0.964894***	0.94947***	0.86484***	0.85393***
ARCH(1)(α)	0.051864***	0.046528***	0.059458***	0.17509***	0***.13657
Leverage	0.10378***	−0.0050305***	−0.032386***	−0.09581***	0.019011***
D of	5.3535	7.0072	7.1542	5.5121	2.8793

Note: ***, ** and * represent significatively at 1%, 5% and 10% statistical levels respectively.

4. Results

The hypotheses that allow us to verify whether Brent can serve as a hedge and/or a safe haven against currencies are:

Hypothesis 1: $\tau_{Brent/i} \leq 0$: Brent is a hedge. Hypothesis 2: $\lambda_u = 0$ and/or $\lambda_L = 0$ Brent is a safe haven. Where $\tau_{Brent/i}$ is the Kendall tau among the Brent and other currencies (i).

λ_u and λ_L are the upper and lower tail dependence for the joint distribution of Brent and one of the other currencies. For more details show Boubaker and Sghaier, (2013), Boubaker and Raza, (2016), Ghorbel et al. (2017) and Karmous et al. (2021).

The vine copula emerges as a highly advantageous model for dependency structures. The incorporation of temporal characteristics into pair copula parameters allows for the variation of each conditional pair copula over time, particularly when they pertain to a family of parameter copulas. Commencing with the Kendall's tau matrix as a criterion for tree selection, this measure of concordance assesses dependence based on ranks. The summation of the absolute values of all Kendall's tau yields the initial root node variable for the D-Vine copula. We opt for the pair that captures the highest dependency in the first tree, as illustrated in the table below, complemented by a scatter plot matrix.

Table 9 shows that the CAD/USD exchange rate has the greatest dependence in all cases. Consequently, CAD/USD is the first root node (1), RUB/USD (2), EUR/USD (3), CNY/USD (4) and BRENT (5).

Table 9. Empirical Kendall's tau τ matrix for returns (Full Sample).

	BRENT	**EUR/USD**	**CAD/USD**	**RUB/USD**	**CNY/USD**
BRENT	1.00000000	−0.04937662	−0.24996598	−0.25604329	−0.09268464
EUR/USD	−0.04937662	1.00000000	0.29936901	0.13379245	0.25492254
CAD/USD	−0.24996598	0.29936901	1.00000000	0.2909988	0.2270470
RUB/USD	−0.25604329	0.13379245	0.2909988	1.00000000	0.1582451
CNY/USD	−0.09268464	0.25492254	0.2270470	0.1582451	1.00000000

The **Table 9** and the **Figure 3** show that the BRENT has a strong association with CAD/USD and RUB/USD exchange rates ($|\tau_{CAD}|$ = 0.25 and $|\tau_{RUB}|$ = 0.26). While, the BRENT has a feeble association with EUR/USD and CNY/USD. We also notice that there is an interrelation among the exchange rates. We note CAD/USD and EUR/USD have a strong connection ($|\tau_{CAD\ EUR}|$ = 0.30), as well as CAD/USD and RUB/USD ($|\tau_{CAD\ RUB}|$ = 0.29). We conclude that there is an association among the BRENT and oil-exporting countries more than importing countries.

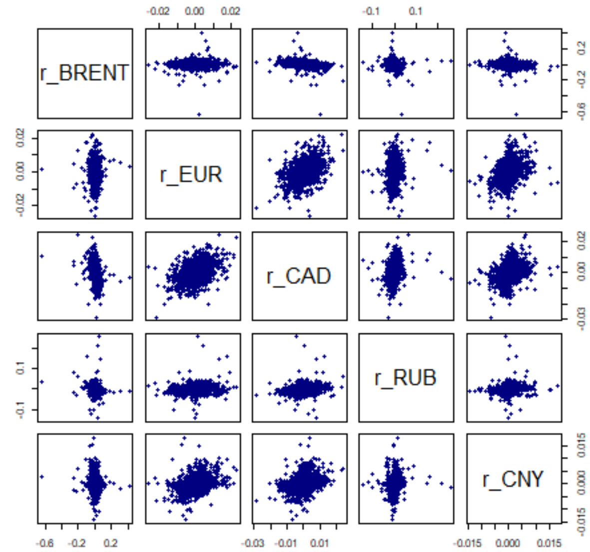

Figure 3. Scatter plot matrix of the returns.

4.1. D-Vine estimation

According to Czado et al. (2012) initial, we perform sequential maximum likelihood estimation to obtain initial values for the D-Vine copulas. Next, using the initial values from the first step, we apply maximum likelihood estimation (MLE) to estimate the final parameters of the paired copula. **Table 10** show parameter estimates for D-vine respectively with their trees.

Table 10. Results of estimated parameters for the D-vine copula (Full Sample).

Tree	Edge	Family	Parameter1 $\boldsymbol{\theta_1}$	Parameter2 $\boldsymbol{\theta_2}$	Tau $\boldsymbol{\tau}$	Lower Tail dependence $\boldsymbol{\lambda_u}$	Upper Tail dependence $\boldsymbol{\lambda_L}$
1	3,4	t-Sudent	0.38	11.55	0.25	0.03	0.03
	1,3	t-Sudent	0.45	5.19	0.30	0.18	0.18
	2,1	t-Sudent	0.43	5.23	0.29	0.17	0.17
	5,2	t-Student	−0.39	3.59	−0.26	0.03	0.03
2	1,4;3	Frank	1.28	0.00	0.14	-	-
	2,3;1	t-Student	0.02	5.99	0.01	0.04	0.04
	5,1;2	t-Student	−0.25	28.52	−0.16	0.00	0.00
3	2,4;1,3	Frank	0.65	0.00	0.07	-	-
	5,3;4,2	Gaussian	0.13	0.00	0.09	-	-
4	5,4;2,1,3	Rotated Joe 90°	−1.03	0.00	−0.02	-	-

The results of D-Vine show that most of the pairs give us t-Student and Frank copula.

In the initial D-Vine tree, it is evident that there exists an inverse relationship between the brent and RUB/USD pair. Additionally, there is a favorable correlation among currencies, characterized by symmetric tail dependence in all pairs, as dictated by the student-t copula. In the second tree, an adverse correlation is observed between Brent and CAD/USD under the condition of RUB/USD, with a symmetric tail dependence governed by the student-t copula. Concerning EUR/USD and RUB/USD, conditional on CAD/USD, a mild positive correlation is evident, characterized by symmetric tail dependence in both upper and lower tails, as dictated by the t-student copula. Moreover, there exists a positive correlation, guided by the Frank copula, between CAD/USD and CNY/USD under the condition of EUR/USD and CAD/USD. Moving to the third tree, there is a subtle correlation between RUB/USD and CNY/USD conditional on EUR/USD and CAD/USD, dictated by the Frank copula. Additionally, a weak correlation is observed between Brent and EUR/USD conditional on RUB/USD and CAD/USD. In the fourth tree, a mild and adverse correlation is noticed between Brent and CNY/USD under the condition of EUR/USD, RUB/USD, and CAD/USD, guided by the Rotated Joe 90 degrees copula (refer to **Figure 4**).

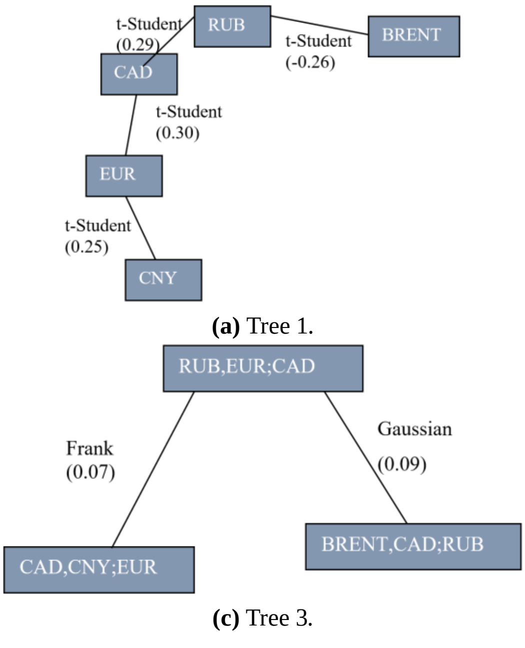

Figure 4. Plot of D-vine copula trees (Full Sample).

4.2. Crisis period analysis

In the subsequent section, our attention will be directed towards two critical phases: the period encompassing the COVID-19 pandemic (from December 2019 to April 2021) and the Russia-Ukraine invasion (from February 2022 to October 2022). We will replicate the identical methodology employed in the full sample analysis for these two crisis periods.

Concerning the COVID-19 pandemic, the new order of nodes determined by the empirical kendall's tau matrix is:

- Order(1): CAD/USD;
- Order(2): RUB/USD;
- Order(3): CNY/USD;
- Order(4): BRENT/USD;
- Order(5): EUR/USD.

The outcomes from the D-Vine model reveal that a majority of the pairs are characterized by t-Student and Rotated Joe 90° copulas. It is noteworthy that, even amidst the COVID-19 crisis, the correlation between Brent crude oil and all currencies remains both weak and negative. Additionally, Brent exhibits a higher correlation with the exchange rates of oil-exporting nations, with values of −0.25 and −0.26 concerning the Russian ruble and Canadian dollar, respectively, in comparison to those of importing countries (−0.04 and −0.09 with EUR and the Chinese Yuan, respectively). Moreover, the correlation between RUB and CNY conditional on Brent remains positive but has experienced an augmentation during the COVID-19 crisis (from 0.13 to 0.21), accompanied by a lower tail dependence indicated by the Rotated Gumbel 180 degrees copula. This trend is similarly observed in the correlation between RUB and EUR conditional on Brent and that between RUB and CAD conditional on Brent, which have increased from 0.13 to 0.15 and from 0.22 to 0.30, respectively. Consequently, it is evident that the dependency between Brent and all currencies has intensified during the COVID-19 crisis period.

Concerning the Russia Ukraine, the new order of nodes determined by the empirical Kendall's tau matrix is:

- Order(1): CAD/US/USD;
- Order(2): EUR/USD;
- Order(3): BRENT/USD;
- Order(4): CNY/USD;
- Order(5): RUB/USD.

Tables 11 and **12** depict that the correlation between Brent crude oil and all currencies maintains a negative trend, with a notable surge during the Russian invasion of Ukraine. Particularly, noteworthy is the correlation between Brent and the Russian ruble, which has shifted from negative (−0.26) to positive (0.06), albeit remaining very weak. Furthermore, there is a discernible increase in the correlation among exchange rates during the crisis. For instance, the dependency between EUR and the Canadian dollar escalated from 0.30 to 0.44.

Table 11. Results of estimated parameters for the D-vine copula (COVID-19 Pandemic period).

Tree	Edge	Family	Parameter1 θ_1	Parameter2 θ_2	Tau τ	Lower Tail dependence λ_u	Upper Tail dependence λ_L
1	4,3	Rotated Joe 90°	−1.17	0.00	−0.09	-	-
	2,4	t-Sudent	−0.39	3.48	−0.25	0.03	0.03
	1,2	t-Sudent	0.53	3.79	0.36	0.28	0.28
	5,1	t-Student	0.49	3.61	0.32	0.27	0.27
2	2,3;4	Rotated Gumbel 180°	1.26	0.00	0.21	-	0.27
	1,4;2	Rotated Joe 270°	−1.20	0.00	−0.10	-	-
	5,2;1	Rotated Joe 90°	−1.08	0.00	−0.04	-	-
3	1,3;2,4	Frank	1.76	0.00	0.19	-	-
	5,4;1,2	Joe	1.18	0.00	0.09	0.20	-
4	5,3;1,2,4	Gaussian	0.24	0.00	0.15	-	-

Table 12. Results of estimated parameters for the D-vine copula (period Russia's invasion Ukraine).

Tree	Edge	Family	Parameter1 θ_1	Parameter2 θ_2	Tau τ	Lower Tail dependence λ_u	Upper Tail dependence λ_L
1	3,5	t-Student	0.10	3.21	0.06	0.13	0.13
	1,3	Rotated Gumbel 90°	−1.28	0.00	−0.22	-	-
	2,1	Gaussian	0.64	0.00	0.44	-	-
	4,2	Gaussian	0.49	0.00	0.33	-	-
2	1,5;3	Rotated Joe 180°	1.09	0.00	0.05	-	0.11
	2,3;1	Rotated Gumbel 180°	1.12	0.00	0.10	-	0.14
	4,1;2	Frank	1.30	0.00	0.14	-	-
3	2,5;1,3	Gaussian	0.19	0.00	0.12	-	-
	4,3;2,1	Rotated Gumbel 270°	−1.06	0.00	−0.06	-	-
4	4,5;2,1,3	Rotated Joe 90°	−1.05	0.00	−0.03	-	-

5. Conclusion and discussion

From a global trade finance standpoint, the relationship between oil and currency holds paramount importance. Noteworthy is that substantial shifts in crude oil prices or the U.S. dollar's value led to simultaneous movements in major currency pairs extensively utilized by both oil-exporting and oil-importing nations. Beyond its economic and geopolitical dimensions, comprehending the intricacies of the interplay between foreign exchange and crude oil markets bears significant implications for traders and regulatory bodies. Consequently, investors and other stakeholders in the market are actively exploring diverse risk management strategies to mitigate and diversify risks inherent in both markets.

In this research, our objective was to explore the dynamics between Brent crude oil and various currencies. Additionally, we sought to investigate whether crude oil prices could serve as a hedge, safe haven, and diversification factor for traditional currencies. To achieve this, we employed a copula approach, providing a more nuanced understanding of the interdependence among different financial instruments. Initially, we applied the ARMA-GARCH model to our return data, Subsequently, for multivariate analysis, we estimated D-Vine copula using an ordinal estimation method. The dependencies among variables were simultaneously analyzed and information criteria guided the selection of the model that best suited our data. Once the appropriate Vine model was chosen, we delved into examining the rank correlation and tail dependence coefficients separately to understand the hedging and safe-haven aspects of Brent crude oil.

It is observed that Brent crude oil exhibits a negative correlation with all currencies throughout the entire sample period. To elaborate further, the negative correlation is more pronounced with the Canadian dollar and Russian ruble compared to the Euro and Chinese Yuan. This implies that Brent demonstrates a stronger negative correlation with the exchange rates of oil-exporting nations than with those of oil-importing nations. Consequently, over the full sample duration, Brent serves as a robust hedge and safe haven against currency fluctuations, particularly in the context of exporting countries such as Canada and Russia.

In the analysis of the crisis periods, particularly during the COVID-19 pandemic, the interrelated movements among the variables exhibited heightened levels compared to the entire sample period. Notably, the negative dependence between Brent crude oil and all currencies persisted, reaffirming Brent's substantial role as a robust hedge and a reliable safe haven against currency fluctuations. Similarly, amid the Russia-Ukraine conflict, the collective movement of all variables remained elevated, and the correlation between Brent crude oil and various currencies retained its negative trend. It's noteworthy that the dependence between Brent and the Russian ruble became exceptionally positive and weak during this crisis. Consequently, the findings indicate that fluctuations in Brent oil prices correlate with currency depreciation (appreciation) in countries functioning as net oil exporters and importers, both in the broader sample and crisis contexts. This implies that an increase (decrease) in oil prices corresponds to a rise (fall) in the value of the U.S. dollar.

Ultimately, the outcomes of our analysis provide valuable insights for traders seeking to navigate the foreign exchange market amid crisis situations. By discerning patterns of currency appreciation and depreciation influenced by oil prices during these tumultuous times, traders can strategically capitalize on optimal trading opportunities. The consistent findings throughout our study underscore the enduring role of Brent crude oil as a robust hedge and reliable safe haven, particularly when confronted with heightened market volatility. This information equips traders with a deeper understanding of how oil prices interact with currency dynamics, enabling them to make informed decisions and enhance their risk management strategies in the face of market uncertainties.

The results suggest that Brent Crude Oil has a negative correlation with all currencies during the full sample period, as well as during the COVID-19 pandemic and Russia's invasion of Ukraine. This confirmation of the role of Brent Crude Oil as a hedge and a safe haven against the fluctuations of major currencies. We also observe that oil remains a strong hedge and safe haven during the crisis, with co-movements higher in all countries than during the entire sample period which is also confirmed by Akalpler and Bakar (2018), Jiang et al. (2020), Beckmann et al. (2020), and Tiwari et al. (2024).

Furthermore, our empirical estimations show that there is an exceptionally positive correlation between Brent and the Russian ruble during the Russia-Ukraine crisis, which confirms that oil is a poor hedge and a weak safe haven against the Russian ruble. The correlation between oil prices and currency values is a crucial aspect of international economics. It is worth mentioning that significant movements in the price of oil or the value of the U.S. dollar cause simultaneous responses in the major currency pairs widely used by oil-exporting and oil-importing nations. Brent oil plays a significant role as a hedge and refuge against currency fluctuations. This study reveals that Brent has a negative correlation with all major currencies, making it an effective hedge against currency fluctuations, specifically for oil-exporting countries such as Canada and Russia which is in contradiction with Mikhaylov et al. (2024) results who find that the Russian ruble exchange rate may not have fully reflected the impact of recent shocks, including those in 2008, 2012, and 2020 caused by the COVID-19 pandemic.

During periods of crisis such as the COVID-19 pandemic and the Russia-Ukraine conflict, oil and currency price movements are more interdependent. In spite of this, the negative correlation of Brent with major currencies persists, strengthening Brent's role as a hedge and safe haven, although exceptions such as the exceptional positive correlation between Brent and the Russian ruble can occur during periods of geopolitical crisis which aligns with the results of Su et al. (2020).

The empirical results provide support for the relevance of some dates and events in the relationship between exchange rates and oil markets. It can be argued that the persistent exchange rate volatility during turbulent periods is exacerbated by changes in international oil prices. The exchange rate is an important channel for the transmission of oil price shocks to capital markets and the real economy, so the issue is whether monetary policy should take climate change into account for its transmission channels.

Author contributions: Conceptualization, HB and MBSZ; methodology, MBSZ; software, HB; validation, HB and MBSZ; formal analysis, HB; investigation, HB; resources, HB; data curation, HB; writing—original draft preparation, MBSZ; writing—review and editing, MBSZ; visualization, MBSZ; supervision, HB. All authors have read and agreed to the published version of the manuscript.

Conflict of interest: The authors declare no conflict of interest.

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