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Time Varying Dependance between Crude Oil, Natural Gas and OPEC and NON-OPEC Exchange Rate Using Wavelet Vine Copula

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Abstract

In this paper, we explore the dynamic relationship between exchange rates, natural gas, and crude oil prices using the wavelet vine copula approach. The vine copula method offers the advantage of capturing key characteristics of changes in petroleum prices. We examine the out-of-sample hedging effectiveness of two popular vine copula models: canonical (C) and drawable (D) vine copulas. Vine copula modeling provides greater flexibility and allows for the modeling of complex dependency patterns in high-dimensional distributions. Analyzing daily return data for WTI, Brent, natural gas, and the SAR, KWD, MXN, and EUR exchange rates, we find evidence of asymmetric links between these variables. The empirical results indicate that the C-vine copula model is the most effective in detecting the dependence between different variables. Overall, our findings suggest that for long-term investors, the relatively strong co-movement over the long term reduces diversification benefits between these assets. In contrast, for short-term investors, investing in crude oil is a favorable option due to its low correlation with stock returns. However, investors should be cautious about the increased co-movement during crisis periods, as it indicates a higher risk of contagion.

Keywords

Dependence, Exchange Rates, Crude Oil Price, Natural Gas, Wavelet Vine Copula

1. Introduction

Exchange rates have a significant contagious effect on commodities markets. Research by Kumar et al. (2021) shows that exchange rates transmit shocks from one commodities market to another, playing a crucial role in transferring the effects of commodity prices to economies. Moreover, fluctuations in exchange rates can lead to volatility in commodity prices, especially in globally traded commodities like oil, gas, and metals, where prices are often denominated in major currencies such as the U.S. dollar. This connection highlights the importance of exchange rates as a key driver in the dynamics of energy commodity prices (Lioudis, 2018).

In the previous several decades, the energy sector (crude oil and natural gas) has been subject to various shocks and periods of volatility. As an important resource for the global economy, the research is motivated by the impact of these shocks on the exchange rate and economics. Due to its leading position among energy commodities, crude oil is the most susceptible asset to geopolitical, health, and economic developments. For example, the political unrest in the Middle East region, the global financial crisis, and most recently, the emergence of COVID-19 are the primary causes of crude oil price volatility throughout these periods. The fall of energy and currency prices precipitated by the most recent health pandemic, Covid-19, was the most severe of any previous crises, including the 2008 global financial crisis. In November 2020, the price of crude oil in this epidemic hit its lowest point. Harvey (2020) asserts that the present financial crisis has resulted in "Great Compression", and Mhalla (2020) demonstrates that it has raised market worries and policy uncertainty.

The cost of manufacturing, interest rates, and inflation are only some of the ways that energy price shocks may impact economic growth and exchange rates (Mensi et al., 2021b). Due to the increased demand for energy futures as a hedging mechanism against the exchange rate, studying the volatility spillovers between energy prices and the exchange rate is crucial for the growth of financial markets and the management of investment portfolios. Oil-exchange rate relationships have been the subject of several empirical investigations (Jain & Biswal, 2016; Kumar et al., 2021). Existing research mainly focuses on oil prices and exchange rates, with mixed findings (Xu et al., 2019). For instance, Basher et al. (2012) demonstrated that a positive oil price shock could decrease the US dollar exchange rate of developing countries in the short term, while Yang et al. (2017) showed a negative correlation between crude oil prices and exchange rates for oil-exporting nations. Albulescu & Ajmi (2021) concluded that there is bidirectional effect between US exchange rate and oil price especially during the financial crisis 2008-2009. Additionally, studies by Jiang (2020) and Khraief et al. (2021) highlighted the asymmetric effects of crude oil prices on exchange rates.

The relationship between exchange rates and natural gas markets has received less attention compared to crude oil, yet it plays a crucial role in understanding global financial dynamics, especially for energy-exporting countries. Exchange rates can act as a key transmission mechanism for spillover effects between natural gas markets and broader economies, influencing the cost of imports and exports, investment decisions, and overall market stability. It is suggested that exchange rates can impact natural gas prices by altering the competitiveness of exports, especially for countries that are major producers or consumers of natural gas. For instance, depreciation in the currency of a natural gas-exporting country could make its exports cheaper, potentially increasing demand and influencing global natural gas prices. Conversely, for energy-importing countries, fluctuations in exchange rates can affect the cost of natural gas imports, thereby impacting inflation and economic stability. However, the literature on this subject is limited and on specific case of energy importing countries (Kumar et al., 2021; Jalal & Gopinathan, 2023, He et al., 2019). Research on natural gas spillovers often focuses on its link with crude oil, highlighting the interconnectedness of these energy markets (Mensi et al., 2021b; Kumar et al., 2019; Li et al., 2019).

Given the emerging complexities of global energy markets and the increasing importance of natural gas as a cleaner alternative to other fossil fuels, there is a growing need to explore the dynamic interactions between oil price, natural gas prices and exchange rates. Understanding these spillover effects is particularly important for policymakers and investors who need to manage risks associated with currency fluctuations and energy price volatility. Advanced modeling techniques that capture the time-varying and nonlinear nature of these relationships, such as wavelet-vine copula approaches could provide deeper insights into how exchange rate movements impact natural gas markets and vice versa.

In summary, the spillover between exchange rates and natural gas markets is an underexplored area that warrants further investigation. Expanding the research in this domain will contribute to a more comprehensive understanding of energy-financial interdependencies, offering valuable information for risk management, strategic planning, and economic policy formulation in a globalized and volatile economic landscape. Recent energy and exchange rate volatility, however, has left the argument regarding energy-exchange rate spillovers wide open and calls for more investigation across various nations. Spillovers are intricately linked to hedging strategies and portfolio risk management.

The primary purpose of this article is to conduct a comprehensive study of the interconnectedness and mutual impact of crude oil, natural gas, and currency exchange rates. This article also analyzes the hedging and safe-haven effectiveness of crude oil, natural gas, and currency exchange rates.

Our addition to existing research can be understood from several angles. This research explores the link between oil prices, natural gas prices, and exchange rates in some of the largest oil and gas-producing OPEC and non-OPEC nations to get a complete conclusion regarding this relationship. Second, we do not only examine the link between oil and exchange rate as previous research, but we also examine the multidirectional interaction between natural gas, crude oil, and the exchange rate. The considerable transition from crude oil to natural gas as a cleaner source of energy and a crucial means of reducing CO_2 emissions makes the incorporation of natural gas as an energy resource crucial. In addition, studying the multidirectional relationships between these factors would assist in determining which portfolio component would serve as a safe haven. The safe-haven component would sidestep the hazards caused by the volatility of other components; hence, the addition of safe-haven asset prices to a portfolio would reduce investment risk. This research would determine which asset would reduce the risk of portfolios including energy prices (crude oil and natural gas) and exchange rate indices, particularly during the present volatility of the energy and exchange rate markets. Third, to test the heterogeneous market hypothesis that there is a difference between the investment behavior of short-term investors (e.g. speculators) and long-term investors (e.g. institutional investors), we employ the Wavelet-Vine copula approach to examine the energy-stock market dependence at different time investment horizons. This approach aids in separating the raw series into short-run and long-run components and demonstrates the reliance between the upper and lower tail distributions by using copulas with varying parameters.

2. Literature Review

Energy is one of the most financially significant commodities because of its importance to the global economy. Energy's price, production cost, and interest rate effect stock markets. Crude oil and natural gas markets, sensitive to economic and geopolitical variables, are volatile and unpredictable. Energy-exporting and energy-importing nations' economies and financial markets suffer from energy market volatility. Thus, recent literature emphasizes the need of monitoring energy-financial spillovers amid instability.

Several study techniques have been devised in order to investigate the spillover impact that exists between crude oil, natural gas, and the stock market. On the other hand, the literature about the spillover effect that exists between energy and exchange rate is still scarce. Bouri et al. (2017) used the cross-correlation function in order to evaluate the impact that China's reform of oil prices in 2013 had on the risk dynamic that exists between the Chinese stock market and oil prices. After making the necessary adjustments to the pricing of oil on the domestic market, the findings demonstrate a reduced degree of causation in the variation between the international oil market and the Chinese stock market. Ashfaq et al. (2020) use multivariant GARCH techniques to investigate the behavior of the spillover between the oil market and the stock market in a number of Asian nations that are both oil exporters and oil importers. The findings reveal varying degrees of substantial stock-oil shock link among the nations where the effect of the oil shock on oil-exporting nations is greatest. Mensi et al. (2021a) use a time-varying asymmetric model to investigate the asymmetric spillovers that occur between the markets for gold, crude oil, and 10 different sectors of the Chinese stock market. They discovered a large asymmetry as well as time-varying spillovers between the stock and commodities markets. The investigation into the management of portfolios reveals that including commodities in an equity portfolio lowers the overall degree of risk. In the midst of the financial crisis, Belhassine (2020) does an analysis of the mean and volatility spillover impact of oil and stock returns across 19 industries in the Eurozone. The findings, which were obtained using the VAR-BEKK-GARCH approach, indicate that the mean and volatility of the stock market and the oil market are both time-varying and heterogeneous. In addition, the findings strengthen the contagion impact of the global financial crisis, although the spillover effect associated with the euro debt crisis remained unchanged.

Several studies have looked at the ways in which shocks and crises influence the link between the energy and financial markets. According to Guo et al. (2021), the number of people in the market who are willing to take risks during the pandemic is more than the number of people who are unwilling to take risks. As a result, negative shocks may readily magnify the existing risk in the market and spread themselves quickly from one market to another. Bouri et al. (2016) investigate the quantile causation that exists between the price of oil and the returns on the sectoral stocks in Jordan both before and after the political crisis. They demonstrate that various sectoral stocks react in a variety of ways to the shocks in the price of oil and how they are influenced by the political upheaval in 2010. The oil price shock that occurred from 2014-2016 had major repercussions on stock markets, according to Ashfaq et al. (2019). Li & Wei (2018) investigate the relationship between the oil and stock markets by using the variational mode decomposition (VMD) method and a variety of time-varying copulas to data collected both before and after the financial crisis. The findings indicate that the current global financial crisis has strengthened the link between the price of crude oil and the performance of the stock market in China. Furthermore, the results demonstrate the existence of asymmetric risk spillovers between the two markets throughout each subperiod. Okorie & Lin (2022) establish that there is bidirectional spillover between the oil market and the Nigerian stock market by using an asymmetric VAR model. They also demonstrate that the anticipated loss of portfolios is much greater after the crisis and over the course of the long term. According to Ji et al. (2020), the different sorts of shocks that occur in the oil market are responsible for the variances in the stock returns of the BRIC countries related to oil. Wen et al. (2018) show that changes to the way oil prices are set have unique impact on the amount of uncertainty in the Chinese sectoral stock market.

Mensi et al. (2021b) and Kumar et al. (2019) have examined the spillover and interdependence between natural gas and stock markets. Mensi et al. (2021b) investigate the systemic risk between crude oil, natural gas, gasoline, and stock markets in the MENA area using copula functions, the Variational Mode Decomposition (VMD) approach, and the Conditional Value at Risk (CoVaR) metric. The results demonstrate the interdependence structure and systemic risk between MENA stock markets and energy crude oil, natural gas, and gasoline. Kumar et al. (2019) discover an asymmetric time-varying link between oil, natural gas, and the Indian stock market. However, there is no long-term correlation between natural gas or oil prices and stock prices. Li et al. (2019) and Lovcha & Perez-Laborde (2020) analyze the crude oil-natural gas link, respectively. Li et al. (2019) document considerable risk spillovers between crude oil and natural gas at several time scales, while Lovcha & Perez-Laborde (2020) demonstrate the growing frequency of risk spillovers and the interconnectedness of crude oil and natural gas markets. Even after the shale gas revolution, they see a substantial low-frequency connection between both markets.

Global economy and financial markets have been influenced by the latest epidemic. During this new pandemic, a number of research indicate that market dynamics display significant shifts in terms of spillover effects between energy and stock returns. According to Mensi et al. (2021a), the infectious impact of coronavirus is devastating and even has a domino effect. The research by Jebabli et al. (2022) demonstrates that during the current health epidemic, there were more transmissions of volatility between the energy and stock markets than during the 2008 global financial crisis. Using time-varying spillover analysis, Corbet et al. (2020) discovered different fluctuations in the China stock markets and crude oil prices in conjunction with the spread of the Covid-19 virus. Mensi et al. (2021a) demonstrate that asymmetric spillover is more apparent during the health crisis era, showing that negative return stock-commodity spillover is greater than spillover associated with good returns. Mensi et al. (2021a) demonstrate that the COVID-19 crisis has the greatest impact on asymmetric spillovers between the oil price, gold price, and Chinese stock market, followed by the global financial crisis (GFC) and the latest oil price shock.

Extensive research has been conducted on the relationship between oil and the stock market. Little consideration has been given to the interactions between energy and exchange rate. The exchange rate is suggested as a transmission mechanism that transmits shock from one commodities market to another (Kumar et al, 2021). The exchange rate also plays a role in transferring the effect of commodities prices to economies. In addition, the exchange rate is a significant factor in the price changes of energy commodities (Lioudis, 2018). In contrast, the research on this topic focuses mostly on the relationship between oil price and exchange rate, and the findings are equivocal (Xu et al., 2019). Using structural VAR, Basher et al. (2012) demonstrate that a positive oil price shock would reduce the US dollar exchange rate of developing countries in the near term. Using wavelet coherence analysis, Yang et al. (2017) demonstrate a negative link between crude oil price and exchange rate for oil-exporting nations. According to this analysis, however, the relationship between oil and currency rate remains questionable for oil-importing nations. Jiang (2020) and Khraief et al. (2021) document the asymmetric effect of crude oil prices on the currency rate. This demonstrates the significance of analyzing the interaction between variables within a nonlinear framework.

Research methods used to examine the connectedness between markets have varied, including Wavelet analysis (Yang et al., 2017), time-varying approaches (Corbet et al., 2020), VAR-based models (Basher et al., 2012; Okorie & Lin, 2020), Copula function (Mensi et al., 2021b), and GARCH family models (Belhassine, 2020; Ashfaq et al., 2020). While these models are useful, they often fall short in capturing the dynamic and periodic characteristics of spillover effects across different time and frequency domains. Recognizing this limitation, Ji et al. (2020) introduced an innovative approach that combines wavelet and vine copula techniques. This method allows for a more nuanced analysis of market dependencies by capturing connections at different time horizons, thus offering a more comprehensive understanding of spillover effects in both time and frequency domains.

In sum, extensive research has examined the interconnectedness and spillover effects between energy markets and financial markets, primarily focusing on crude oil, natural gas, and stocks. Various methodologies, have been employed to capture the complex and evolving nature of these relationships. The findings consistently demonstrate that energy market volatility can have profound effects on stock markets, with the degree of impact varying across different sectors and countries. This is particularly evident during periods of economic instability, such as financial crises or pandemics, where spillover effects become more pronounced and asymmetric, reflecting heightened risk transmission across markets.

While significant strides have been made in understanding the spillover effects between energy and stock markets, there is a notable gap in the literature regarding the interactions between energy markets and exchange rates. Although some studies suggest that exchange rates act as a transmission mechanism for shocks between commodity markets and broader economies, the relationship between energy prices and exchange rates, especially for oil-importing versus oil-exporting nations, remains unclear and warrants further investigation. Moreover, existing studies have predominantly employed traditional models, which may not fully capture the dynamic and periodic characteristics of spillover effects across different time and frequency domains. Innovative approaches, such as the combination of Wavelet and Vine Copula techniques, offer more nuanced insights into market dependencies by accommodating complex structures and nonlinear relationships that traditional models may overlook.

The last decade has been marked by several shocks and economic crises. Consequently, it is crucial for portfolio managers to comprehend how energy price volatility affects the currency rate in oil-exporting nations. This research would analyze the link between oil price, natural gas price, and exchange rate in OPEC and non-OPEC nations over the time. In contrast to research that analyze the bidirectional link between crude oil and exchange rate, this study examines the multidirectional interaction between natural gas, crude oil, and exchange rate. Examining the multidirectional relationships between these factors would assist determine which portfolio component would serve as a safe haven. The safe-haven component would sidestep the hazards caused by the volatility of other components; hence, the addition of safe-haven asset prices to a portfolio would reduce investment risk. This research would determine which asset would reduce the risk of portfolios including energy prices (crude oil and natural gas) and exchange rate indices, particularly during the present volatility of the energy and exchange rate markets. To test the heterogeneous market hypothesis that there is a difference in the investment behavior of short-term investors (e.g. speculators) and long-term investors (e.g. institutional investors), we employ the Wavelet-Vine copula approach to examine the energy-stock market dependence at different time investment horizons. This approach aids in separating the raw series into short-run and long-run components and demonstrates the reliance between the upper and lower tail distributions by using copulas with varying parameters (Ji et al., 2020).

3. Methodology

We analyze the relationship between oil prices, natural gas, and exchange rates for both OPEC and Non-OPEC countries. Copula models are used to capture the dependency structure among financial assets, largely due to the insights provided by Sklar's theorem (Sklar, 1959). Copulas are particularly useful for measuring the extreme dependence between two random variables. However, a key challenge is selecting the appropriate copula families for higher-dimensional scenarios. Research, such as that by Brechmann & Schepsmeier (2012), has shown that standard multivariate copulas like the multivariate Gaussian or Student-t, as well as Archimedean copulas, lack the flexibility needed to model dependence among a larger number of variables accurately. While some generalizations offer improvements, they often become complex and come with limitations like parameter restrictions.

To address these issues, vine copulas have been developed as a practical solution. They enhance the copula method by accommodating a wide range of dependencies, offering greater flexibility in both lower and upper tail dependence, handling larger dimensions, and providing computationally feasible density estimations.

3.1. Data

The data consists of crude oil prices and nominal exchange rates in US dollars (USD) for the period from April 23, 2012, to January 28, 2022. The exchange rates represent the amount of USD per unit of currency for OPEC and non-OPEC countries involved in international trade, including the Euro (EUR), Mexican Peso (MXN), Saudi Arabian Riyal (SAR), and Kuwaiti Dinar (KWD). An increase in these nominal exchange rates indicates a depreciation of the US dollar relative to foreign currencies. The data is collected on a daily basis. For oil prices, the study uses two key benchmarks: West Texas Intermediate (WTI) from Cushing, the Brent crude from the North Sea and the natural gas (GAS). All data were collected from Datastream. In this study, prices are expressed in logarithmic form, with the first difference (innovation) of prices representing the return on assets.

$$R_{i,t} = 100 * \log\left(\frac{P_{i.t}}{P_{i,t-1}}\right), i = 1, 2, \cdots \quad (1)$$

where $R_{i,t}$ = daily return on asset; $P_{i,t}$ = price of asset at t.

3.2. Models

3.2.1 Model for Marginal Distribution

GJR-GARCH model

The marginal distribution for EUR, MXN, KWD, SAR, **Natural** gas, Brent and WTI are specified as AR(1)-GJR(1,1)-skewed-t model.

$$R_{i,t} = \mu_i + \varphi_i R_{i,t} + \varepsilon_{i,t} \tag{2}$$

$$\varepsilon_{i,t} = \sigma_{i,t} z_{i,t} \tag{3}$$

$$\sigma_{i,t}^2 = \omega_i + \alpha_{i,1}\varepsilon_{i,t-1}^2 + \beta_i \sigma_{i,t-1}^2 + \alpha_{i,2} I_{i,t-1}\varepsilon_{i,t-1}^2 \tag{4}$$

$$z_{i,t} \sim \text{skewed-t}\left(z_{i,t} \mid \eta_i, \varphi_i\right) \tag{5}$$

with i = EUR, MXN, KWD, SAR, Brent, Natural gas and WTI.

First equation: we found $\varepsilon_{i,t}$ the innovation parameter and μ_i is a constant, one lag of $R_{i,t}$ to check assets returns' serial correlations.

Second equation: we showed the residual, which is the product of innovation and conditional volatility.

Thirst equation: we showed that when $\varepsilon_{i,t-1}$ is negative, the leverage term is in charge for catch the leverage effect with $I_{i,t-1} = 1$; else $I_{i,t-1} = 0$.

Fourth equation: supposes standardized residuals to pursue the skewed-t distribution of Hansen (1994).

According to Bastianin (2009), fat tails and asymmetry are significant deviations from normality. The preferred extension of both normal and Student-t distributions is the skewed-t density. While the Student-t density can address excess kurtosis, the skewed-t density is capable of capturing both skewness and kurtosis.

EGARCH model

Nelson (1991); Nelson & Cao (1992) proposed the EGARCH model. They found that there are many advantages of EGARCH model such as:

On the contrary to the GARCH, the EGARCH does not impose any constrains on the parameters, and.

The EGARCH models specified above allow for oscillatory behavior in the conditional variance since the β coefficient can be either negative or positive. $|\beta| < 1$ ensures stationarity and ergodicity for the EGARCH(p,q) (Nelson, 1991).

Using EGARCH model we can show if shocks have symmetric or asymmetric effects on volatility. This effect is captured by γ: $\gamma > 0$, so positive shocks provide rise to higher volatility than negative shocks, and vice versa.

The variance equation for the EGARCH model has the form:

$$\log\left(\sigma_t^2\right) = \omega + \alpha\left(\left|\frac{\varepsilon_{t-p}}{\sigma_{t-q}}\right| - E\left|\frac{\varepsilon_{t-p}}{\sigma_{t-q}}\right|\right) + \gamma\frac{\varepsilon_{t-p}}{\sigma_{t-q}} + \beta\log\left(\sigma_{t-q}^2\right) \tag{6}$$

APARCH model

Ding et al. (1993) present Asymmetric Power ARCH model (APARCH). The specification of this model is can well express the leverage effects, fat tails and excess kurtosis.

$$\sigma_t^2 = \omega + \sum_{j=1}^{q}\alpha_j\left(\left|\varepsilon_{t-j}\right| - \gamma_j\varepsilon_{t-j}\right)^\delta + \sum_{i=1}^{p}\beta_i\left(\sigma_{t-i}\right)^\delta \tag{7}$$

$$\varepsilon_t = \sigma_t z_t,\ z_t \sim N\left(0,1\right) \tag{8}$$

$$k\left(\varepsilon_{t-j}\right) = \left|\varepsilon_{t-j}\right| - \gamma_j\varepsilon_{t-j} \tag{9}$$

γ_j, reflects the leverage effect. $\gamma_j > 0$ indicates negative information has stronger impact on the positive information on the price volatility.

The APARCH equation is assumed to satisfy the following conditions.

1) $\omega > 0$, $\alpha_j \geq 0$, $j = 1, 2, \cdots, q$, $\beta_i \geq 0$, $i = 1, 2, \cdots, p$, when $\alpha_j = 0$, $j = 1, 2, \cdots, q$, $\beta_i = 0$, $i = 1, 2, \cdots, p$ then $\sigma_t^2 = \omega$. Due to the variance is positive, so $\omega > 0$.

2) $0 \leq \sum_{j=1}^{q} \alpha_j + \sum_{i=1}^{p} \beta_i \leq 1$.

3.2.2. Wavelet

The main goal of examining the correlation between oil prices and exchange rates, as well as oil prices and stock markets, is to determine whether oil prices lead to changes in exchange rates or stock markets, or vice versa. We employed wavelet correlation to explore this relationship. The wavelet method assesses how closely two series move together and captures both time-varying and frequency-varying characteristics. A coherence value close to one indicates a strong common behavior between the time series, while a value near zero suggests a lack of coherence. We use wavelet phase differences to differentiate between negative and positive correlations.

The key advantage of the wavelet approach is its ability to perform localized analysis of time series, allowing for examination of index returns and oil prices across different frequency bands. Additionally, the wavelet method is particularly effective for analyzing non-stationary variables. It provides insights into spillover effects across international stock and commodity markets, revealing potential spillovers and contagion. In other words, the wavelet approach is valuable for portfolio diversification and risk management.

Wavelet functions are composed of scale parameters, location, and a mother wavelet function ($\psi \in L^2(\mathbb{R})$) defined as

$$\psi_{\tau,s}(t) = \frac{1}{\sqrt{|s|}} \psi\left(\frac{t-\tau}{s}\right), s, \tau \in \mathbb{R}, s \neq 0 \tag{10}$$

where:

- $\frac{1}{\sqrt{|s|}}$ represent a normalization factor guaranteeing unit variance of the wavelet and

$$\left\|\psi_{\tau,s}\right\|^2 = 1$$

- S is a scaling factor that controls the width of the wavelet, scale has an inverse relation to frequency. A higher scale indicates a stretched wavelet that is suitable for detection of a lower frequency.
- τ is a conversion parameter that controls the location of the wavelet.

There are various types of wavelets, but this study focuses on wavelet coherence (WTC), as defined by Torrence & Compo (1998) and Aguiar-Conraria et al. (2008). WTC is expressed as the ratio of the cross-spectrum to the product of the individual spectra of each time series. It can be considered a measure of the local correlation between two time series in the time-frequency domain.

According to (Torrence & Compo, 1998), WTC can be defined by

$$R_{xy}^2 = \frac{\left|SW_{xy}\right|^2}{S\left(\left|W_x\right|^2\right)S\left(\left|W_y\right|^2\right)} \tag{11}$$

where S is a sleeking operator in both scale and time. Noticeably, R_{xy}^2 close to one indicates evidence of strong correlation whereas R_{xy}^2 close to zero provides a weak correlation.

We assess the statistical significance of the wavelet coherence (WTC) level using Monte Carlo methods, as the theoretical distribution for WTC is not established (Grinsted et al., 2004). The squared WTC alone cannot distinguish between negative and positive correlations. To identify these correlations and the lag-lead relationship between two time series as a function of frequency, we use the phase difference tool.

In our study, we interpret phase differences based on the direction of arrows in the WTC plots. Arrows pointing left or right indicate that the two time series are out of phase or in phase, respectively. Arrows pointing up or down signify causality between the variables, with arrows pointing directly down (or up) showing that the first variable\(y(t)\) is lagging (or leading) the second variable.

3.2.3. Vine Copula

Vine copulas were first introduced by Joe (1996) and later expanded by Bedford & Cooke (2001, 2002) and Kurowicka & Cooke (2006). They offer a flexible approach to modeling multivariate dependence (Nikoloulopoulos et al., 2012). As noted by Czado et al. (2013), vine copulas come in various specifications that allow for modeling bivariate dependence at different levels. These copulas can be illustrated through a hierarchical structure: at the first tree level, four nodes connected by edges represent the dependence between two variables, and at subsequent tree levels, new nodes are derived from the edges of the previous level. In our study, we employed C- and D-vine copulas, each with different hierarchical tree structures.

The three-dimensional density function of the C-vine model is given by:

$$\begin{aligned} f\left(x_1,x_2,x_3\right) &= \prod_{k=1}^{3} f_k\left(x_k\right) \prod_{h=2}^{3} c_{1,h}\left(F_1\left(x_1\right),F_h\left(x_h\right)\right) \\ &\times \prod_{j=2}^{3-1} \prod_{i=1}^{3-j} c_{j,j+1|1,\cdots,j-1}\left(F\left(x_j \mid x_1,\cdots,x_{j-1}\right),F\left(x_{j+1} \mid x_1,\cdots,x_{j-1}\right)\right) \end{aligned} \tag{12}$$

where, $c_{j,j+1|1,\cdots,j-1}$ is the conditional copula and where the conditional distribution function of the x_j variable, given the variable x_j, is given by Joe (1997);

$$F_{i|j}\left(x_i \mid x_j\right) = \frac{\partial C_{ij}\left(F_i\left(x_i\right),F_j\left(x_j\right)\right)}{\partial F_j\left(x_j\right)}$$

"**Figure 1** illustrates the C-vine dependence decomposition organized in a hierarchical tree structure, where each tree (T) follows a star pattern. In this configuration, one variable acts as the central or pivotal element, with the dependence of the other variables measured relative to this key variable, using bivariate copulas as indicated by the second term in Equation (1).

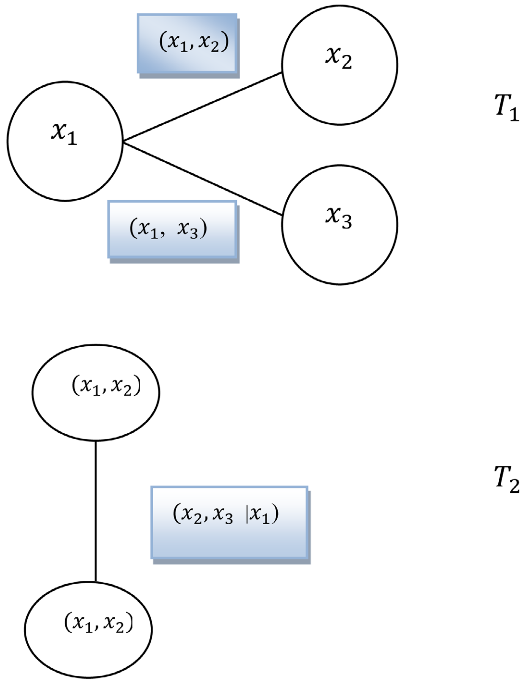


Figure 1. Hierarchical tree structure for the C-vine copula with three variables.

The three-dimensional density function of D-vine model is given by:

$$
\begin{aligned}
f\left(x_1,x_2,x_3\right) &= \prod_{k=1}^{3} f_k\left(x_k\right)\prod_{h=2}^{3} c_{h,h+1}\left(F_h\left(x_{1h}\right),F_{h+1}\left(x_{h+1}\right)\right) \\
&\times \prod_{j=2}^{3-1}\prod_{i=1}^{3-j} c_{i,i+j|1,\cdots,i+j-1}\left(F\left(x_i \mid x_{i+1},\cdots,x_{i+j-1}\right),F\left(x_{i+j} \mid x_{i+j},\cdots,x_{i+j-1}\right)\right)
\end{aligned}
\tag{13}
$$

Figure 2 depicts the hierarchical dependence structure of the D-vine copula, where all variables are treated equally. The order of the variables in the first tree determines the bivariate dependencies in the subsequent trees. The order in the first tree is chosen to capture the maximum possible dependence."

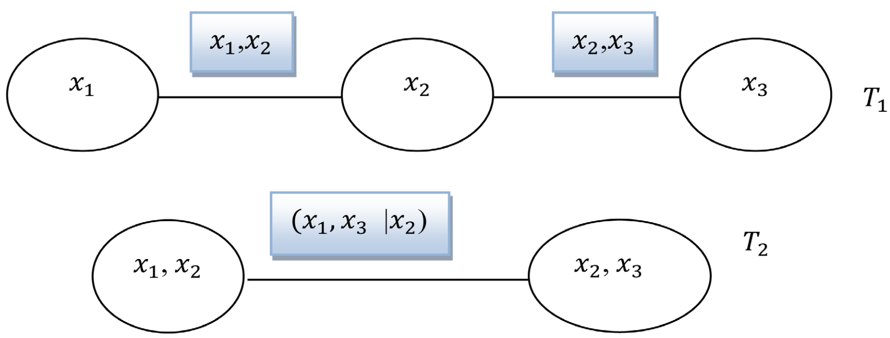


Figure 2. Hierarchical tree structure for the D-vine copula with three variables.

4. Empirical Results

This paper examines the relationship between oil prices, natural gas, and exchange rates from April 23, 2012, to January 28, 2022. We use daily prices for WTI, Brent, and natural gas to represent the energy market, and track exchange rates for MXN, EURO, SAR, and KWD. An increase in these nominal exchange rates indicates a strengthening of the USD relative to other currencies.

Among the variables, WTI exhibits the highest variability compared to Brent, natural gas, and the exchange rates (see Table 1). Mean returns are generally close to zero, with excess kurtosis and negative skewness observed, except for natural gas, MXN, EUR, and SAR exchange rates. The series display fat tails, and the Jarque-Bera test rejects the normality hypothesis. Additionally, the Ljung-Box statistic reveals serial correlation in all series except Brent, WTI, EUR, and MXN. The Lagrange multiplier test for conditional heteroscedasticity indicates ARCH effects in all return series except WTI, supporting our choice to use a GARCH model for filtering the daily returns.

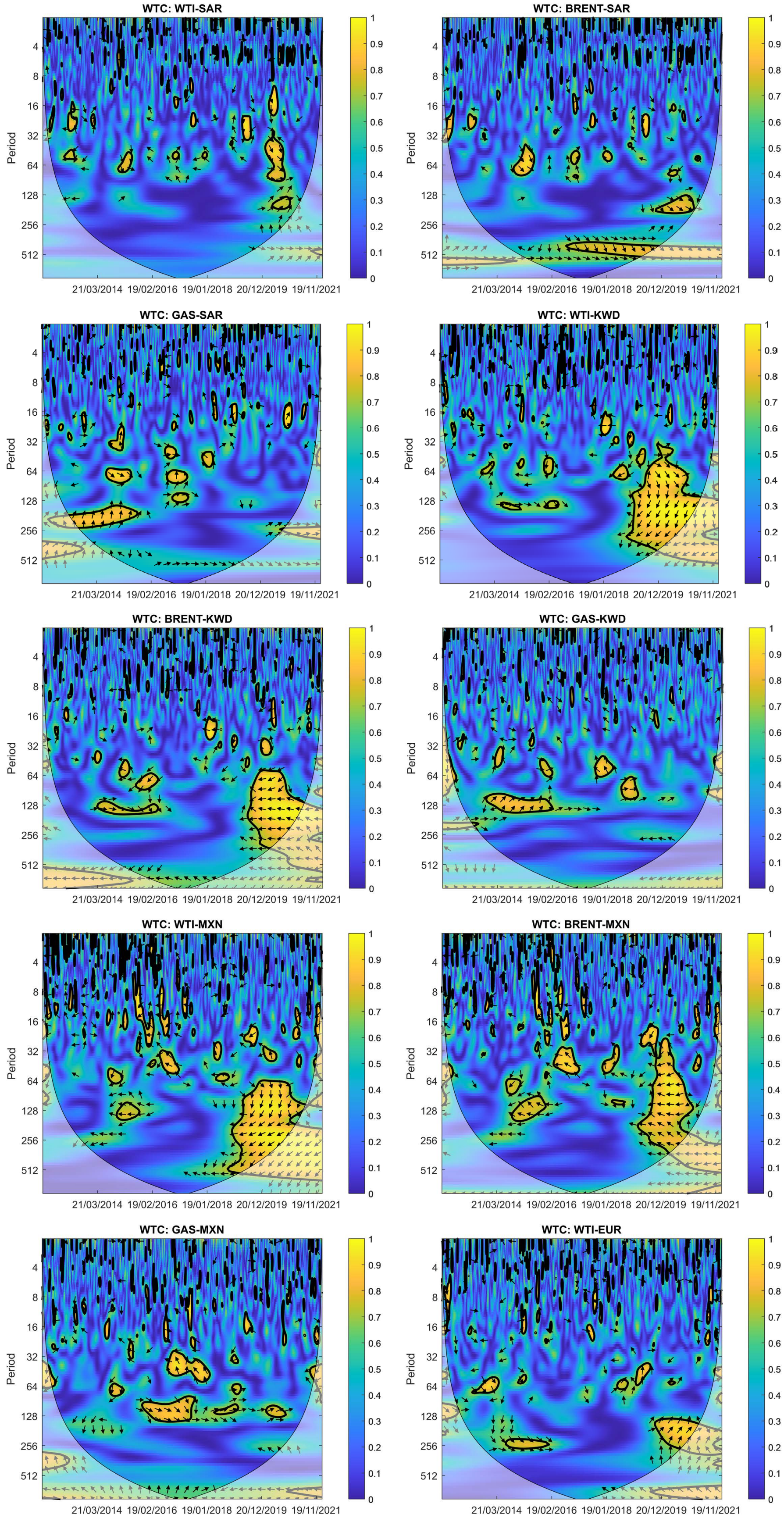
Table 1. Descriptive statistics.

Variable	Statistic characteristics							
	Mean	Median	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	Autocorrelation	ARCH-LM
BRENT	−0.000103	0.000000	0.023437	−0.986757	24.488	49473.07***	2.0471	261.46***
WTI	−0.000689	0.000106	0.049986	−27.31610	1134.693	1.36E+08***	16.623***	6.4135
GAS	0.000348	0.000000	0.033251	0.380252	21.41965	36110.31***	29.058***	528.21***
SAR	−1.72E−07	0.000000	0.003940	0.007864	846.2004	75542363***	652.04***	1150.7***
KWD	3.38E−05	0.000000	0.001554	−0.238716	49.27266	227522.3***	365.77***	1421.4***
EUR	−6.62E−05	−1.08E−05	0.004906	0.047136	6.290092	1151.069***	5.4758*	104.6***
MXN	0.000180	−1.54E−05	0.007763	0.889634	11.12912	7357.649***	0.1585	188.73***

4.1. Wavelet Approach

The wavelet findings as shown in Figure 3 illustrate the wavelet coherence between WTI and the return markets of OPEC and Non-OPEC countries. The 95% confidence intervals are shown by black contour lines, with the horizontal axis representing the study period in days and the vertical axis representing frequency. The color gradient ranges from blue, indicating low coherence, to yellow, indicating high coherence. The lighter black line demarcates the high-power state and the "cone of influence", where edge effects become significant. The direction of the arrows reveals the phase relationships and lead-lag connections between oil prices or gas and exchange rates.

Arrows pointing to the right indicate that the variables are in phase, while arrows pointing to the left indicate they are out of phase. Arrows pointing left-up or right-down suggest that crude oil, gas, or Brent leads the exchange rates, whereas left-down or right-up arrows indicate that these commodities lag behind the exchange rates. In-phase areas suggest a cyclical interaction, while anti-phase areas indicate an anti-cyclical effect. Regions with stronger interdependence imply that crude oil (WTI, Brent) or gas has less potential as a safe haven or hedge for exchange rates, reducing the benefits of including crude oil in exchange rate portfolios.


WTC: WTI-SAR
WTC: BRENT-SAR
WTC: GAS-SAR
WTC: WTI-KWD
WTC: BRENT-KWD
WTC: GAS-KWD
WTC: WTI-MXN
WTC: BRENT-MXN
WTC: GAS-MXN
WTC: WTI-EUR
Period
4
8
16
32
64
128
256
512
21/03/2014 19/02/2016 19/01/2018 20/12/2019 19/11/2021
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1

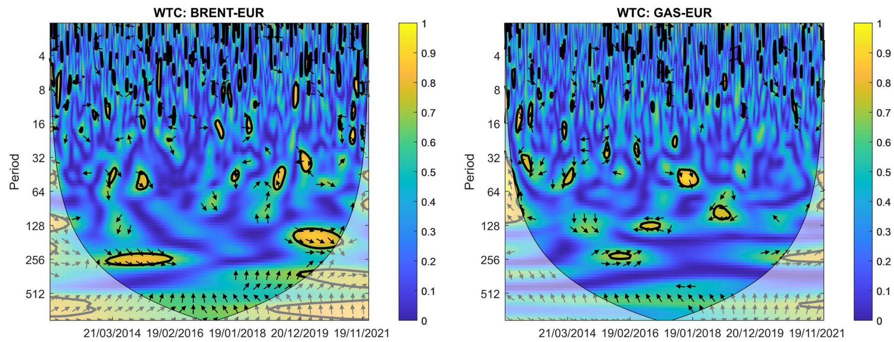


Figure 3. Wavelet OPEC and NON-OPEC countries.

For OPEC countries, the figure shows a high level of out-of-phase co-movement in the long-term frequency band (256 - 512 days). The yellow regions at the bottom indicate strong co-movement between WTI-KWD, Brent-SAR, and Brent-KWD at high frequencies. Arrows oriented left for Brent-KWD and WTI-KWD suggest that oil prices and exchange rates are out of phase, except for SAR. This indicates a negative relationship where increases in oil prices are associated with decreases in the exchange rate relative to the US dollar. The currencies of Kuwait, in particular, show a stronger connection to changes in crude oil prices. At shorter periods (0 to 32 days), the co-movement between crude oil and exchange rates is generally low. In the medium term (32 to 128 days), high co-movement is observed during economic crises such as Brazil's in 2014, Argentina's in 2018, the COVID-19 crisis in 2020, and the global energy crisis in 2021. Brent leads SAR and gas also leads SAR, while WTI lags KWD and Brent, with gas leading KWD.

For Non-OPEC countries, the figure shows that interdependence is higher in the long-term compared to the short-term scales during 2019-2021. During this period, arrows pointing left and down indicate that WTI-MXN and Brent-MXN have a lagging relationship with exchange rates, while arrows pointing right and down show that gas leads the MXN exchange rate. For EUR, the interdependence between Brent-EUR, WTI-EUR, and GAS-EUR is weak in the short term but stronger in the medium and long term. Arrows pointing left and up for WTI-EUR indicate that WTI leads EUR, with similar results for GAS-EUR and Brent-EUR.

The differing interdependence between OPEC and Non-OPEC countries highlights that variations in oil and gas prices significantly influence exchange rates in both regions. Overall, the results suggest a strong but uneven relationship across countries during the COVID-19 and energy crises.

4.2. Wavelet Vine Copula

First, we filter the series using the GJR-GARCH, EGARCH, TGARCH, and APARCH models, which offer advantages over the standard GARCH model. According to the minimum BIC and AIC criteria, the C-vine copula model provides a better fit for both OPEC and Non-OPEC countries with oil prices across all periods. The Vuong test, which assesses whether the C-vine and D-vine copula models are statistically equivalent, did not differentiate between the two models. Therefore, both vine copula specifications are deemed suitable for capturing the multivariate dependence between returns. Data (https://docs.google.com/spreadsheets/d/1FaK-fsVagZb7ExBhhrfPS3j2dyQ_YBxp/edit?usp=drive_link&ouid=111356315669939292266&rtpof=true&sd=true) present the estimated parameters for the D-vine and C-vine copulas, respectively. The optimal C-vine copulas are SBB8 and Tawn90, while the optimal D-vine copulas are Tawn90 and T.

In the short- and mid-term frequencies, and before the crisis, for OPEC countries, conditioning on the KWD exchange rate results in a decrease in both lower and upper tail dependence between SAR-WTI and SAR-Brent. Similarly, conditioning on the SAR exchange rate causes a decrease in tail dependence between GAS and KWD. For WTI, Kendall's tau for $C_{(SAR, WTI)}$ and $C_{(SAR, WTI/Brent)}$ are 0.19 and 0.17, with lower and upper tail dependencies of 0.23 and 0, and 0.20 and 0, respectively. For Brent, Kendall's tau for $C_{(SAR, Brent)}$ and $C_{(SAR, Brent/KWD)}$ are 0.08 and −0.17, with lower and upper tail dependencies of 0.17 and 0, and 0 and 0, respectively. For GAS, Kendall's tau for $C_{(GAS, KWD)}$ and $C_{(KWD, GAS/SAR)}$ are −0.04 and −0.04, indicating no tail dependence, meaning that negative and positive shocks do not simultaneously affect these variables. The KWD has a notable effect on the tail dependence of WTI and Brent with exchange rates, leading to minimal tail dependence when KWD is the conditioning variable.

For Non-OPEC countries, results differ: for WTI, Kendall's tau for $C_{(EUR, WTI)}$ and $C_{(EUR, WTI/MXN)}$ are 0.14 and 0.01, with lower and upper tail dependencies of 0 and 0.01, and 0.28 and 0, respectively. During the Covid crisis, conditioning on the SAR exchange rate causes a decrease in tail dependence between WTI-KWD and Brent-KWD, while conditioning on GAS results in decreased tail dependence between KWD-SAR.

In the mid- and long-term frequencies, and before the crisis, for OPEC countries, conditioning on the KWD exchange rate leads to a reduction in lower and upper tail dependence between SAR-WTI and SAR-Brent. Similarly, conditioning on the SAR exchange rate results in decreased tail dependence between Brent and KWD, and GAS and KWD. For SAR-WTI and SAR-WTI/KWD, no tail dependence is observed, indicating that shocks do not simultaneously affect these variables. Non-OPEC countries also show a significant effect on tail dependence between WTI and exchange rates, and Brent and exchange rates. When conditioning on KWD, tail dependences between oil prices and exchange rates diminish. However, for Non-OPEC countries, results vary: Kendall's tau for WTI's relationship with EUR and MXN show minimal dependence. During the Covid crisis, conditioning on SAR reduces tail dependence between WTI-KWD and Brent-KWD, while conditioning on GAS decreases tail dependence between KWD-SAR.

5. Conclusion

This paper explores the role of safe haven assets in financial markets, providing evidence that such assets can offer significant benefits to investors. The study specifically examines whether oil or natural gas can serve as a safe haven asset. It distinguishes a safe haven asset from hedge and diversifier assets, which may offer average diversification benefits but do not necessarily provide protection during periods of market distress.

The study models the dependence between oil prices and exchange rates, as well as between natural gas and exchange rates, using wavelet vine copulas. Initially, the return series were filtered using an asymmetric GARCH model with a skewed-t distribution. The analysis, based on daily observations from April 23, 2012, to January 28, 2022, revealed skewness, excess kurtosis, and non-normal distribution across all variables. Hence, the copula model was deemed appropriate for capturing the relationships between the variables, as it does not assume linear correlation.

The C-vine copula model was found to provide a better fit for the data, as determined by the minimum BIC and AIC criteria. After identifying structural changes in exchange rates, both D- and C-vine copulas were estimated for each sub-period to assess the impact of these changes on variable dependence. The results indicate that both C- and D-vine copulas are well-suited for modeling the multivariate dependence between return series over the entire sample period.

Empirically, the study finds that oil functions as a safe haven for exchange rates, while natural gas does not serve as a safe haven for bonds in any market. Over the long term, oil remains a safe haven; investors who hold oil for more than 128 trading days after an extreme negative shock generally experience losses. This suggests that investors should consider buying oil during extreme negative returns and selling it once market confidence and volatility stabilize. The results also highlight a significant difference in outcomes based on whether investors consistently hold oil or only purchase it following an extreme negative shock, with the latter strategy diminishing portfolio value.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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