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**Article**

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# Analyzing shifts in structural dependence between oil prices and exchange rates in oil-importing economies

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## Abstract

**Purpose** – The primary purpose of this study is to unveil the relationship between oil prices and exchange rates, with a specific focus on five major oil-importing countries. By examining this relationship, the research aims to provide valuable insights for policymakers, investors and stakeholders operating in the global economic landscape.

**Design/methodology/approach** – The study employs a methodological approach to ensure robust and reliable findings. First, we assess the stationarity of the time series data to establish a solid analytical foundation. Subsequently, we construct GARCH(1,1) models to capture the persistence of the volatilities inherent in the data. Building upon this, we propose the novel application of the Markov-switching R-vine copula approach, which enables us to capture structural changes and measure the dependencies between oil prices and exchange rates.

**Findings** – Our findings uncover significant negative relationships between oil prices and exchange rates across the examined economies while revealing varying degrees of interdependency among these variables. Notably, we elucidate distinct tail dependence structures, encompassing both symmetric and asymmetric aspects, which hold profound implications for risk assessment and portfolio management strategies. Furthermore, this study confirms the presence of regime-switching dynamics, elucidating how the co-movement patterns between oil prices and exchange rates evolve across different states or regimes, reflecting the dynamic nature of these interconnected markets.

**Originality/value** – The originality and value of this study lie in its comprehensive approach to understanding the relationship between oil prices and exchange rates. By accounting for structural changes and regime-switching behaviors, the research provides a nuanced understanding of the complex dynamics at play. The novel application of the Markov-switching R-vine copula approach contributes to the methodological advancement in this field of study. Furthermore, the insights derived from this research offer practical implications for policymakers, investors and stakeholders navigating the complexities of the global economic landscape, enabling them to make informed decisions and develop effective strategies to mitigate risks and capitalize on opportunities.

**Keywords** Exchange rate, Oil-importing countries, Regime dependence switching

**Paper type** Research paper

## 1. Introduction

If we likened “oil as the lifeblood of industry” to the era of industrialization, then “oil serving as the driving force behind modern economies and production” aptly characterizes the contemporary world. Oil, a vital energy source, offers distinct advantages over traditional fossil fuels such as coal and natural gas due to its ease of extraction, storage, refinement, and

**JEL Classification** — C58 Financial econometrics, C50 Econometric modeling: General, E37 Prices, Business fluctuations, Cycles: Forecasting and simulation: Models and applications

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transportation. As per the International Energy Agency findings, in 2018, the oil supply comprised 31.6% of the overall energy supply, surpassing coal at 26.9% and natural gas at 22.8%. Although oil's share in the global energy supply has decreased since 1973, when it accounted for 46.2% of the total, it remains the dominant energy source today. Despite significant shifts in the global energy structure, oil prices continue to play a crucial role as a key input in many economic activities. Simultaneously, exchange rates play a pivotal role in a nation's foreign trade and in balancing domestic and foreign economic development. Extensive empirical research has consistently revealed a long-run relationship between oil prices and the real effective exchange rate, as noted by [Amano and Van Norden \(1998\)](#). Both oil prices and exchange rates occupy significant roles in international financial markets, and numerous studies have examined their relationship, producing diverse findings on their co-movements ([Beckmann and Czudaj, 2013](#); [Beckmann et al., 2020](#)). However, it is important to acknowledge that research outcomes have often been inconclusive regarding the strength of this relationship ([Bénassy-Quéré et al., 2007](#)). The variability in outcomes may be due to differences in methodologies, sample periods, and country-specific factors.

This study addresses the challenges posed by nonlinear relationships and structural changes in co-movements by proposing the regime-switching vine copula approach. The core concept of this approach, rooted in Markov chains introduced by [Hamilton \(1989\)](#), has more recently been integrated into copula models, notably the regular vine copula framework, which suits our multidimensional dataset ([Fink et al., 2017](#)). Regular (R)-vines are constructed hierarchically, using bivariate copulas as fundamental building blocks. They have proven to be a viable model for analyzing multidimensional data, with the added benefit of facilitating inference through their hierarchical structure ([Aas et al., 2009](#)). Compared to traditional methods, the R-vine copula model offers several advantages. First, it can effectively represent a joint distribution alongside any univariate distribution, enhancing flexibility in modeling multivariate distributions. Second, even in extreme events, it can capture a broad spectrum of dependence structures, including asymmetric, nonlinear, and tail dependence. This study adopts the methodology outlined by [Fink et al. \(2017\)](#) to investigate the structural dynamics in the co-movement between real oil prices and real effective exchange rates. Specifically, this study focuses on a Markov model with two states, referred to as the “normal” and “abnormal” regimes. This framework enables us to capture the co-movement between real oil prices and real effective exchange rates as they transition from a normal state to an abnormal one, shedding light on how these variables interact across different economic conditions.

While prior research has explored the impact of oil prices on exchange rates, this study distinguishes itself in several key aspects. Firstly, it adopts a novel approach, the regime-switching vine copula method, which differs from previous studies that mainly focused on the direct influence of oil prices on exchange rates, often overlooking potential structural changes in their co-movements. This paper pioneers the application of the Markov-switching R-vine copula model to analyze the relationship between real oil prices and real exchange rates, particularly in the context of five oil-importing nations. What sets this study apart is its exploration of the effectiveness of the regime-switching R-vine approach, a novel angle that has not been previously investigated. Furthermore, it marks the first instance of applying a Markov regime-switching vine copula model to the nexus between oil prices and exchange rates in larger importing oil-producing countries. Previous research, such as [Pastpipatkul et al. \(2015\)](#) and [Aloui and Aïssa \(2016\)](#), primarily delved into the dynamic relationships among energy, stock, and currency markets using canonical (C)-vines and drawable (D)-vines copula models. [Stöber and Czado \(2014\)](#) focused on modeling nine daily exchange rates using an R-vine approach, while [Gurgul and Machno \(2016\)](#) explored sovereign CDS markets in G7 and BRICS, alongside crude oil, gold, stock indices, exchange rates, freight indices, and copper prices through dynamic R-vine copulas.

Notably, prior research in the domain of regime-switching multivariate copulas has been relatively limited, with most studies concentrating on the bivariate case—analyzing pairs of markets at a time—even when examining a sizable group of countries. Therefore, this study

contributes to the field by adopting a fresh perspective, encompassing larger oil-importing nations, and exploring the regime-switching vine copula methodology to shed new light on the complex relationship between oil prices and exchange rates, accounting for nonlinearities and structural changes.

The relationship between oil prices and exchange rates is crucial in international economics. For oil-importing countries, higher oil prices typically lead to currency depreciation due to worsening trade balances and inflationary pressures, while the opposite often occurs for oil exporters. However, this relationship is complex and non-linear, influenced by economic structure, monetary policy, and global conditions. Our study employs a regime-switching vine copula model to capture these dynamics, focusing on “low dependence” and “high dependence” regimes. These regimes represent periods of varying correlation between oil prices and exchange rates, with switches potentially triggered by global economic shocks, oil market changes, policy shifts, or geopolitical events. Our sample includes five major economies: the United States, India, China, Japan, and Korea. These countries were chosen for their significant oil consumption relative to GDP, comparable economic development, and active participation in global trade. Despite four being Asian, the US is included due to its global economic influence and recent transition from major oil importer to significant producer following the fracking revolution. This study aims to provide valuable insights into the intricate dynamics between oil prices and exchange rates, crucial for policymakers, investors, and economists in understanding international financial interactions.

The remainder of this paper is organized as follows: [Section 2](#) provides literature review, [Section 3](#) illustrates the data and econometric methods adopted. [Section 4](#) describes the data’s characteristics and presents the empirical results. [Section 5](#) concludes the paper.

## 2. Literature review

Copula models are popular tools in financial econometrics for modeling dependencies between random variables. In the context of oil prices and exchange rates, the copula model is particularly valuable because it allows for the capture of nonlinear dependencies, which are common in financial markets. These models separate the marginal distributions of individual variables from their dependency structure, making them ideal for analyzing complex relationships that change across different market conditions.

Many studies used copula models in the oil price-exchange rate nexus have found that the relationship between these two variables often exhibits asymmetric behavior and tail dependencies. For example, [Chen \*et al.\* \(2016\)](#) and [Bai and Lam \(2019\)](#) used a copula-GARCH model to show that oil price shocks, particularly during periods of heightened volatility, have a pronounced and nonlinear impact on exchange rates. This model captures how extreme changes in oil prices (e.g. due to geopolitical events or sudden supply shocks) can lead to significant movements in exchange rates, a relationship that linear models might miss. Similarly, [Sebai and Naoui \(2015\)](#) used a copula approach combined with a DCC-MGARCH model, emphasizing the tail dependencies between oil prices and exchange rates during market stress.

While basic copula models are effective in capturing the dependence between two variables, financial markets often involve interactions between multiple variables. This is where the Vine copula model proves beneficial. Vine copulas extend traditional copulas by modeling dependencies in a hierarchical structure, which allows for the decomposition of complex multivariate relationships into a series of bivariate copulas ([Bedford and Cooke, 2002](#)). Three types of Vine copulas, *ce*, are commonly used in empirical research. These models provide a more flexible and intricate structure that does not impose a specific dependency order, making them suitable for scenarios where relationships among variables are not clearly defined ([Aas \*et al.\*, 2009](#)).

Several researchers have utilized Vine copulas to explore dependencies among financial variables. For instance, Pourkhanali *et al.* (2016) applied R-Vine copulas to measure financial risk, while Czado *et al.* (2022) employed D-Vine and R-Vine copulas to examine the dependence between individual stocks related to ESG factors and their broader markets. In the context of the oil and exchange rate nexus, studies by Pastipatkul *et al.* (2015), Aloui and Aïssa (2016), and He *et al.* (2021) have also applied Vine copulas. However, despite their advantages, Vine copulas do not account for structural changes in the relationships between variables, such as those driven by geopolitical events, economic crises, or major policy shifts. These structural changes are particularly important in the oil price-exchange rate nexus, where shifts in market regimes—such as periods of low versus high volatility—can drastically alter the dependencies between variables. For example, during an oil price shock, the relationship between oil prices and exchange rates may change abruptly, a scenario where Vine copulas struggle to capture these sudden shifts.

To address the limitation of traditional Vine copulas, the Markov-Switching Vine copula (MS-Vine copula) has been proposed. This model incorporates a regime-switching mechanism, allowing the dependency structure to change across different market states or regimes (Stöber and Czado, 2014). This is particularly useful in the context of oil prices and exchange rates, where the dependency structure can shift between low-volatility (stable) and high-volatility (crisis) periods (Fink *et al.*, 2017). Research has shown that regime-switching models, such as the MS-Vine copula, are effective in capturing changes in dependencies due to structural breaks and market turbulence (Evkaya *et al.*, 2024).

While the application of MS-Vine copulas is growing in areas such as stock market analysis and risk management (Mudiangombe and Muteba Mwamba, 2022; Soury, 2024), their use in the oil price-exchange rate nexus remains relatively limited. However, the model holds great potential for analyzing oil-importing nations, where fluctuations in oil prices can significantly and abruptly impact exchange rates (Narayan and Narayan, 2007). In such countries, the exchange rate is particularly sensitive to oil price changes. For instance, when oil prices rise, the local currency may depreciate due to higher import costs, and vice versa. The MS-Vine copula model is well-suited to capturing these shifts, as it can model changes in the dependency structure across different regimes, providing more accurate risk assessments and policy recommendations.

### 3. Data and methodology

#### 3.1 Data

The dataset used in this study comprises monthly data from January 2007 to December 2020. It focuses on the real effective exchange rates (REER), with the base index set at 2010 = 100, for oil-importing countries. Specifically, the dataset includes five countries: the United States (EUS), India (EIN), China (ECN), Japan (EJP), and Korea (EKR). The data is sourced from Thomson Reuters Datastream. Additionally, the Europe Brent Spot Price (BRENT), measured in dollars per barrel, is obtained from the U.S. Energy Information Administration (EIA). To facilitate the analysis, the time series data was transformed by computing returns using the logarithmic difference transformation. This comprehensive dataset forms the foundation for our empirical analysis, enabling us to explore the dynamic relationship between real oil prices and real effective exchange rates across these selected oil-importing countries over the specified period.

#### 3.2 Methodology

**3.2.1 The marginal distribution.** The marginal distribution of each market within the dataset is characterized by the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model. The model is extended from Autoregressive Conditional Heteroskedasticity (ARCH) model of Engle and Bollerslev (1986). These models hold significant prominence in

econometrics, particularly in financial time series analysis, as they are instrumental in modeling conditional variance. The GARCH process can be expressed as follows:

$$\begin{aligned} r_t &= \mu + \varepsilon_t, \\ \varepsilon_t &= \eta_t \sigma_t; \eta_t | \Omega_{t-1} \sim (0, 1), \\ \sigma_t^2 &= \alpha_0 + \sum_{i=1}^q \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^p \beta_i \sigma_{t-i}^2, \end{aligned} \quad (1)$$

where  $p$  is the lag order of GARCH term  $\sigma_{t-p}^2$  and  $q$  is the lag order of the ARCH term  $\varepsilon_{t-q}^2$ .  $\omega$  is the constant term of the conditional variance equation.  $\sigma_t$  is the conditional variance and  $\eta_t$  is the standard residual,  $\eta_t = \varepsilon_t / \sqrt{\sigma_t^2}$ .  $\mu$  is the intercept term.

**3.2.2 Regular vine copula.** This section details the Pair Copula Construction (PCC) method and introduces some related concepts. The PCC method, initially proposed by Joe (1997) and further developed by Bedford and Cooke (2002) and Aas and Berg (2013), revolves around the utilization of vine copulas. Vine copulas offer a versatile approach to constructing multidimensional probability distributions. They achieve this by creating a hierarchy of conditional bivariate copulas. The fundamental principle behind this modeling approach lies in factorizing a  $d$ -dimensional copula density into conditional distributions. These conditional distributions are defined using bivariate copulas, which capture the dependency structure between two variables simultaneously. This approach enables a comprehensive and flexible representation of complex dependencies within multivariate datasets, making it a valuable tool in various fields, including econometrics and statistical analysis.

In this study, we adopt a regular vine (R-vine) copula structure due to its flexible nature. For simplicity, let's consider a three-dimensional distribution with marginal density functions  $F_1$ ,  $F_2$  and  $F_3$ . Denote the joint density function as  $f$  which can be expressed as follows:

$$\begin{aligned} f(x_1, x_2, x_3; \theta_1, \theta_2, \theta_3) &= c_{13;2}(F_{1|2}(x_1|x_2), F_{3|2}(x_3|x_2); \theta_1) \\ &\quad \times c_{23}(F_2(x_2), F_3(x_3); \theta_2) c_{12}(F_1(x_1), F_2(x_2); \theta_3) \\ &\quad \times f_3(x_3) f_2(x_2) f_1(x_1), \end{aligned} \quad (2)$$

where  $c_{13;2}$  is the copula density distribution of  $(x_1, x_2)$  conditional on  $x_2$ .  $c_{23}$  is the copula density distribution of  $(x_2, x_3)$  and  $c_{12}$  is the copula density distribution of  $(x_1, x_2)$ .  $\theta_1, \theta_2, \theta_3$  are dependency parameters. It's important to highlight that the multivariate decomposition structure of the R-vine copula is not predetermined. Equation (2) represents just one possible type of the 3-dimensional R-vine decomposition structure. Generally, an  $n$ -dimensional R-vine can be expressed with  $d - 1$  trees. The tree  $T_i$  has  $d - i + 1$  nodes and  $d - i$  edges, and the edges in the tree  $T_i$  will become the nodes in the tree  $T_{i+1}$ . The construction of the R-vine model is referred to Yu et al. (2018).

When estimating R-vines, a diverse set of bivariate copulas can be considered as potential candidates. These copulas cover a broad spectrum, including elliptical copulas such as the Gaussian and Student's  $t$  copulas (discussed by Christoffersen and Langlois (2013)), as well as the Archimedean family of copulas. Examples of copulas within the Archimedean family include Clayton, Gumbel, Frank, Joe, Clayton-Gumbel (BB1), Joe-Clayton (BB7), Joe-Frank (BB8), among others. For a detailed description, readers can refer to Czado et al. (2012). In the context of modeling dependence, nonlinear relationships are frequently quantified using Kendall's  $\tau$  coefficient, as outlined by Czado et al. (2012). Additionally, tail dependence, which characterizes extreme dependencies, is evaluated through the upper and lower tail dependence coefficients, denoted as "upper tail  $\lambda_U$ " and "lower tail,  $\lambda_L$ " respectively. These coefficients play a crucial role in capturing the behavior of copulas in the tails of probability distributions, which is essential for modeling extreme events and risks.

$$\tau = 4 \int \int_{[0,1]^2} C(u_1, u_2) dC(u_1, u_2) - 1 \quad (3)$$

$$\lambda_U = \lim_{u \rightarrow 1} \frac{1 - 2u + C(u, u)}{1 - u} \quad (4)$$

$$\lambda_L = \lim_{u \rightarrow 1} \frac{C(u, u)}{u} \quad (5)$$

**3.2.3 Markov-switching R-vine copula models.** The concept behind Markov-switching models, which was first introduced by [Hamilton \(1989\)](#), revolves around a latent Markov chain that governs a first-order Markov process. In this context, the R-Vine copula, presented in [Eq. \(2\)](#), can be expanded to incorporate Markov-switching dynamics. This extension allows for deriving a joint R-vine copula density function contingent on the prevailing regime, capturing the regime-dependent dependencies among variables.

$$\begin{aligned} f(x_1, x_2, x_3; \theta_1(S_t), \theta_2(S_t), \theta_3(S_t)) &= c_{13|2}(F_{1|2}(x_1|x_2), F_{3|2}(x_3|x_2); \theta_1(S_t)) \\ &\times c_{23}(F_2(x_2), F_3(x_3); \theta_2(S_t)) c_{12}(F_1(x_1), F_2(x_2); \theta_3(S_t)) \\ &\times f_3(x_3) f_2(x_2) f_1(x_1), \end{aligned} \quad (6)$$

where  $S_t = \{1, 2\}$  serves as a representation of a Markov chain, essentially signifying the distinct hidden regimes or states that the time-dependent variable can assume. This state variable adheres to a first-order Markov chain framework and is governed by a probability transition matrix.  $P$

$$p_{ij} = \Pr(S_t = j | S_{t-1} = i) \text{ and } \sum_{j=1}^2 p_{ij} = 1 \quad i, j = 1, 2, \quad (7)$$

where  $p_{ij}$  denote the probability of transitioning from one regime (state) to another as  $p_{\{ij\}}$ , where  $i$  and  $j$  represent the respective regimes. These transition probabilities can be organized into a transition matrix  $P$ , structured as follows:

$$P = \begin{bmatrix} p_{11} & 1 - p_{11} \\ 1 - p_{22} & p_{22} \end{bmatrix}. \quad (8)$$

A two-step estimation method is employed to estimate the parameters of the MS-R-Vine copula model. Firstly, the estimation of the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model is carried out. Subsequently, the optimal parameters obtained from the GARCH process are held fixed in the likelihood estimation of the MS-R-Vine model. In the second step, the remaining dependency parameters of the MS-R-Vine model are estimated. Moreover, the estimation process for this model requires deriving inferences about the probabilistic evolution of the state variable. These probability estimates, commonly known as filtered probabilities, are computed using Hamilton's filter, as detailed in the seminal work by [Hamilton \(1989\)](#). The filtered probabilities provide insights into the likelihood of transitioning between different states or regimes over time, enabling a comprehensive understanding of how the hidden states evolve over time.

## 4. Empirical results

### 4.1 Descriptive statistics

[Table 1](#) summarizes descriptive statistics for the returns of real oil prices and effective exchange rates. Notably, these variables' mean and median returns are approximately centered



Table 1. Descriptive statistics

	Mean	Max	Min	Std. Dev	Skewness	Kurtosis	Jarque-Bera
RBRENT	0.000	0.204	−0.244	0.052	−1.246	9.569	339.390***
RECN	0.001	0.018	−0.014	0.006	−0.034	2.997	0.031
REIN	0.000	0.019	−0.021	0.007	−0.381	3.541	6.001**
REJP	0.000	0.046	−0.030	0.010	0.339	5.317	40.084***
REKR	0.000	0.034	−0.057	0.009	−1.518	13.337	798.046***
REUS	0.000	0.024	−0.014	0.006	0.642	4.499	26.789***

**Note(s):** \*, \*\*, and \*\*\* denote respectively degree of significance at the 10, 5, and 1% levels  
**Source(s):** Author’s calculations based on using R program

around zero, suggesting a balanced distribution of positive and negative returns. Regarding skewness, most returns exhibit negative skewness, indicating that their marginal distributions have a left-tailed shape. It is worth noting that each variable comprises 165 observations, ensuring a consistent dataset. Among these variables, REIR stands out with the highest excess kurtosis, and all kurtosis values are positive. This positive kurtosis signifies that the distribution of returns has heavier tails than a normal distribution, potentially indicating the presence of more extreme values. Additionally, the Jarque-Bera test results reveal that the normality assumption is rejected for all returns except for RECN. This suggests that the distribution of most returns significantly deviates from a normal distribution, highlighting the need for robust statistical methods to capture their underlying behavior. Based on the histograms in Figure 1, we observe several indications that the distributions of our variables deviate from normality. For instance, REIN exhibit skewness, with the data leaning towards one side rather than being symmetrically distributed around the mean, which is a hallmark of non-normality. Additionally, REKR and REUS show signs of heavy tails and sharp peaks, suggesting the presence of kurtosis, where extreme values occur more frequently than in a normal distribution. This further supports the argument for non-normality. The distribution of RBRENT also shows skewness, reinforcing the idea that these variables are not normally distributed.

These visual observations suggest that the dataset may not follow the assumptions of normality, which is important when considering certain statistical models that rely on this assumption.

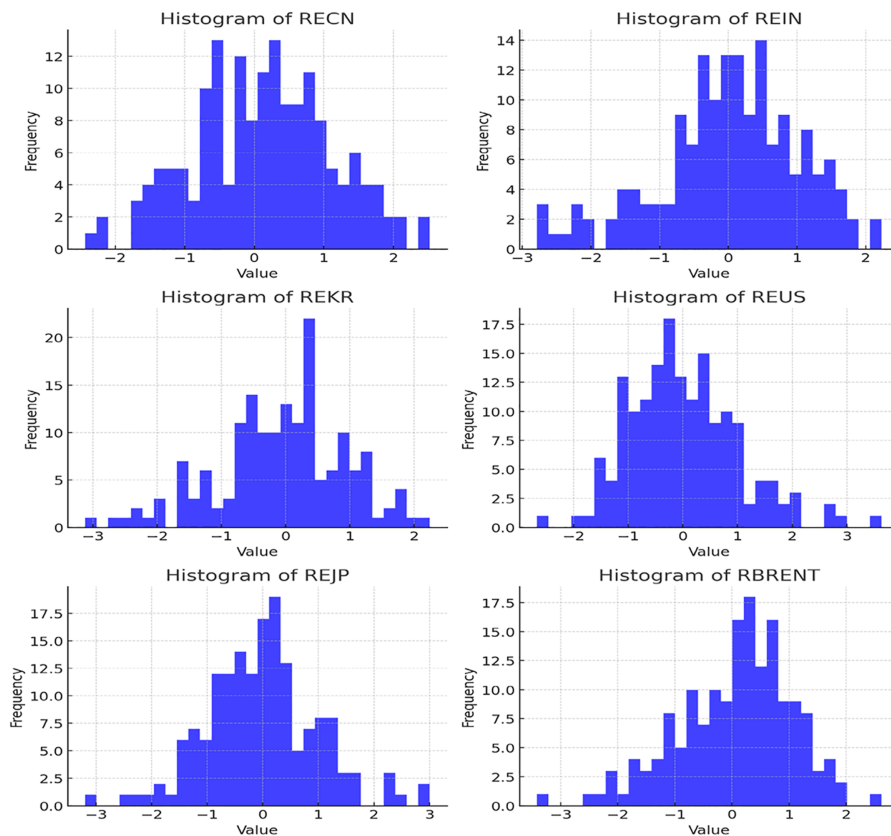
4.2 Unit root test

Table 2 provides the results of stationary tests conducted on the returns of real oil prices and real effective exchange rates. Assessing the stationarity of time series data before proceeding with empirical analysis is imperative. Nonstationary data may exhibit unit roots, making them unsuitable for specific statistical analyses. In this study, the Augmented Dickey-Fuller (ADF) test is employed to examine the returns’ stationarity. The null hypothesis of the ADF test posits that the time series possesses a unit root and is, therefore, nonstationary. However, the *p*-values presented in Table 2 indicate that all returns have *p*-values less than 0.010. This suggests strong evidence against the null hypothesis of unit roots and, in turn, supports the conclusion that the series is stationary. Stationarity is a crucial assumption for various econometric and time series models, ensuring the reliability of subsequent analyses.

4.3 GARCH models

The study compares GARCH(1,1) models that incorporate three distinct probability distributions—normal, student-*t*, and generalized error distribution—to determine the most suitable distribution for modeling real oil prices and effective exchange rates. The optimal distribution is selected based on two widely recognized model selection criteria: the Akaike





**Source(s):** Author's calculations based on using R program

**Figure 1.** The distribution of returns for each respective variable

**Table 2.** ADF test results

Variable	ADF-stat	p-value
RBRENT	-8.728	0.000
RECN	-8.936	0.000
REIN	-11.719	0.000
REJP	-9.510	0.000
REKR	-8.636	0.000
REUS	-8.090	0.000

**Source(s):** Author's calculations based on using R program

Information Criterion (AIC) and the Bayesian Information Criterion (BIC). These criteria are commonly employed to evaluate the relative quality of statistical models and identify the best-fitting distribution for the given data. As displayed in Table 3, the results indicate the best-fitted distribution for each variable. Notably, for most return series, the best-fitted distributions are either normal or Student-t distributions. However, it is worth highlighting that REIN best fits the generalized error distribution, demonstrating the necessity of considering different

**Table 3.** Marginal distribution selection

Variable	AIC Norm	Student-t	GED	BIC Norm	Student-t	GED
RBRENT	-3.758	-3.710	-3.746	-3.645	-3.578	-3.614
REUS	-7.721	-7.730	-7.722	-7.608	-7.598	-7.590
RECN	-7.636	-7.560	-7.631	-7.523	-7.428	-7.499
REIN	-6.971	-7.045	-7.050	-6.858	-6.913	-6.918
REJP	-6.371	-6.379	-6.382	-6.258	-6.247	-6.250
REKR	-6.976	-6.966	-6.968	-6.863	-6.834	-6.837

**Note(s):** Norm is normal distribution, student-t is student-t distribution, and GED is Generalized Error distribution. The italic number indicates the lowest AIC and BIC for each pair

**Source(s):** Author's calculations based on using R program

distributional assumptions for different variables to accurately model their underlying behaviors.

Continuing with the analysis, GARCH(1,1) models are established for each variable return using their respective optimal marginal distributions. The results of these models are presented in Table 4. Notably, the estimates of the GARCH parameters, represented as  $\alpha$  and  $\beta$ , are found to be significant at either the 1% or 5% significance level for most returns, indicating the presence of long-run persistence in their volatilities. When considering the summation of  $\alpha$  and  $\beta$  for each return series, RBRENT stands out with the highest value. This suggests that the volatility of Brent's return exhibits the highest level of persistence among the analyzed variables. Persistence in volatility is a crucial aspect to consider in financial modeling and risk management, as it reflects the degree to which past volatility influences future volatility, and higher persistence can have significant implications for financial decision-making.

#### 4.4 Measuring dependence with vine copula

Following establishing the GARCH(1,1) models, this study derives the standardized residuals, which are subsequently utilized in the R-vine Copula and MS-R-vine Copula models. Various copula functions are considered in constructing the Vine structure, including Gaussian, Student-t, Clayton, Gumbel, Frank, and Joe copulas.

Table 5 presents the results of the R-vine copulas, showcasing Kendall's tau and upper/lower tail dependences for the nexus between oil and exchange rates. Notably, RBRENT exhibits the highest negative relationship with RECN, as indicated by Kendall's tau of  $-0.250$ . Additionally, weak interdependence is observed between RBRENT and REIN within the R-vine structure. Furthermore, two distinct types of tail dependence structures are identified: symmetric tail dependence between RBRENT-REIN, RBRENT-RECN, and REKR-REJP|RECN, RBRENT, REUS; and asymmetric tail dependence involving REUS-REJP

**Table 4.** GARCH Estimation results

Variable	$\mu$	$\omega$	$\alpha$	$\beta$
RBRENT	0.867*** (0.050)	-3.192*** (0.841)	0.267*** (0.074)	0.721*** (0.238)
RECN	0.261 (0.183)	-0.954 (0.648)	0.0725 (0.123)	0.919*** (0.059)
REIN	-0.584 (0.460)	-0.317** (0.130)	0.009*** (0.003)	0.956*** (0.018)
REJP	0.447* (0.233)	-7.481** (3.763)	0.486*** (0.114)	0.234 (0.407)
REKR	-0.231 (0.258)	-0.577** (0.232)	0.087 (0.100)	0.950*** (0.022)
REUS	0.190 (0.188)	-3.304 (3.602)	0.022 (0.166)	0.691** (0.333)

**Note(s):** \*, \*\*, and \*\*\* denote respectively degree of significance at the 10, 5, and 1% levels

**Source(s):** Author's calculations based on using R program

**Table 5.** Results of single-regime R-Vine copula

Pair	Copula	$\theta$	$\lambda$	$\lambda_U$	$\lambda_L$
REUS-REJP	Joe	1.120	0.064	0.143	–
RBRENT-REIN	T	–0.020	0.002	0.039	0.039
RBRENT-REKR	Frank	–0.930	–0.102	–	–
RBRENT-RECN	T	–0.380	–0.250	0.006	0.006
RBRENT-REUS	Gaussian	–0.180	–0.110	–	–
RBRENT-REJP REUS	Frank	–1.700	–0.180	–	–
RECN-REIN RBRENT	Gaussian	–0.130	–0.080	–	–
RECN-REKR RBRENT	Gaussian	–0.160	–0.100	–	–
RECN-REUS RBRENT	Gumbel	1.250	0.200	0.259	–
RECN-REJP RBRENT,REUS	Frank	–1.740	–0.180	–	–
REUS-REIN RECN,RBRENT	Frank	–0.210	–0.020	–	–
REUS-REKR RECN,RBRENT	Frank	–1.000	–0.110	–	–
REKR-REJP RECN,RBRENT,REUS	T	–0.370	–0.240	0.018	0.018
REKR-REIN REUS,RECN,REBENT	Gumbel	1.180	0.150	0.201	–
REIN-REJP REKR,RECN,RBRENT,REUS	Frank	–1.420	–0.150	–	–

**Source(s):** Author's calculations based on using R program

and RECN-REUS|RBRENT, as well as REKR-REIN|REUS, RECN, and RBRENT. These findings shed light on the intricate dependency relationships between the analyzed variables, providing valuable insights for risk assessment and portfolio management.

#### 4.5 Regime-switching Vine copula

In addition to the R-vine Copula analysis, this study establishes the MS-R-Vine model to examine the structural changes in the dynamic co-movement between real oil prices and real effective exchange rates of oil-importing countries. The results of this analysis are reported in [Tables 6 and 7](#), providing insights into how the relationships between these variables evolve across different regimes or states.

**Table 6.** The estimated result of MS-R-Vine in the first regime

Pair	Copula	$\theta$	$\lambda$	$\lambda_U$	$\lambda_L$
REUS-REJP	Joe	1.103	0.055	0.125	–
RBRENT-REIN	T	–0.112	–0.379	0.054	0.054
RBRENT-REKR	Frank	–1.098	–0.120	–	–
RBRENT-RECN	T	–0.108	–0.068	0.055	0.055
RBRENT-REUS	Gaussian	–0.023	–0.014	–	–
RBRENT-REJP REUS	Frank	–1.123	–0.123	–	–
RECN-REIN RBRENT	Gaussian	–0.034	–0.021	–	–
RECN-REKR RBRENT	Gaussian	–0.236	–0.151	–	–
RECN-REUS RBRENT	Gumbel	1.203	0.168	0.221	–
RECN-REJP RBRENT,REUS	Frank	0.739	0.081	–	–
REUS-REIN RECN,RBRENT	Frank	0.018	0.002	–	–
REUS-REKR RECN,RBRENT	Frank	0.521	0.057	–	–
REKR-REJP RECN,RBRENT,REUS	T	0.294	0.189	0.159	0.159
REKR-REIN REUS,RECN,REBENT	Gumbel	1.293	0.226	0.291	–
REIN-REJP REKR,RECN,RBRENT,REUS	Frank	0.029	0.003	–	–

**Note(s):** Abnormal regime or low dependence regime

**Source(s):** Author's calculations based on using R program

**Table 7.** The estimated result of MS-R-Vine in the second regime

Pair	Copula	$\theta$	$\lambda$	$\lambda_U$	$\lambda_L$
REUS-REJP	Joe	1.405	0.186	0.362	–
RBRENT-REIN	T	–0.247	–0.158	0.034	0.034
RBRENT-REKR	Frank	–1.943	–0.207	–	–
RBRENT-RECN	T	–0.334	–0.216	0.024	0.024
RBRENT-REUS	Gaussian	–0.345	–0.224	–	–
RBRENT-REJP REUS	Frank	–2.049	–0.136	–	–
RECN-REIN RBRENT	Gaussian	0.302	0.195	–	–
RECN-REKR RBRENT	Gaussian	–0.019	–0.012	–	–
RECN-REUS RBRENT	Gumbel	1.090	0.082	0.111	–
RECN-REJP RBRENT,REUS	Frank	–2.093	–0.222	–	–
REUS-REIN RECN,RBRENT	Frank	–1.029	–0.113	–	–
REUS-REKR RECN,RBRENT	Frank	1.529	0.025	–	–
REKR-REJP RECN,RBRENT,REUS	T	0.234	0.150	0.138	0.138
REKR-REIN REUS,RECN,REBENT	Gumbel	1.093	0.000	0.114	–
REIN-REJP REKR,RECN,RBRENT,REUS	Frank	2.043	0.085	–	–
$p_{11}$		0.951	0.010		
$p_{22}$		0.982	0.010		

**Note(s):** Normal regime or high dependence regime

**Source(s):** Author’s calculations based on using R program

With a transition probability of 0.951 for regime 1 and 0.982 for regime 2, it suggests that once the financial system enters a specific regime, it has a strong tendency to persist within that regime over time. In practical terms, this means there is a 95.1% chance of staying in the normal regime (regime 1) and a 98.2% chance of remaining in the abnormal regime (regime 2). This high persistence in regime-switching indicates that market conditions tend to remain relatively stable or turbulent for extended periods before transitioning to the other state.

The analysis reveals a consistent negative correlation between oil prices and exchange rates across all currency pairs examined. This inverse relationship aligns with previous studies that have documented the negative impact of oil price increases on the value of currencies, particularly in oil-importing countries (Amano and Van Norden, 1998; Chaudhuri and Daniel, 1998; Beckmann and Czudaj, 2013). As noted by Basher *et al.* (2016), higher oil prices can lead to elevated costs, trade deficits, and inflationary pressures, all of which can contribute to currency depreciation in oil-importing economies.

When comparing the findings between the first and second regimes (Tables 6 and 7), it is observed that the correlation between oil prices and exchange rates is lower in regime 1 compared to regime 2. This distinction between regimes aligns with the concept of regime switching in the dynamics of financial markets, as documented in studies by Engel and Hamilton (1990) and Engel and Hakkio (1996). Regime 1 represents a period of low dependence or an abnormal state, where the relationship between oil prices and exchange rates is weaker or distorted, potentially due to factors such as market interventions, policy shifts, or economic shocks (Beckmann *et al.*, 2020). In contrast, regime 2 is characterized by high dependence or a more normal state, where the negative correlation between oil prices and exchange rates is stronger and more pronounced, reflecting the underlying economic principles and market dynamics.

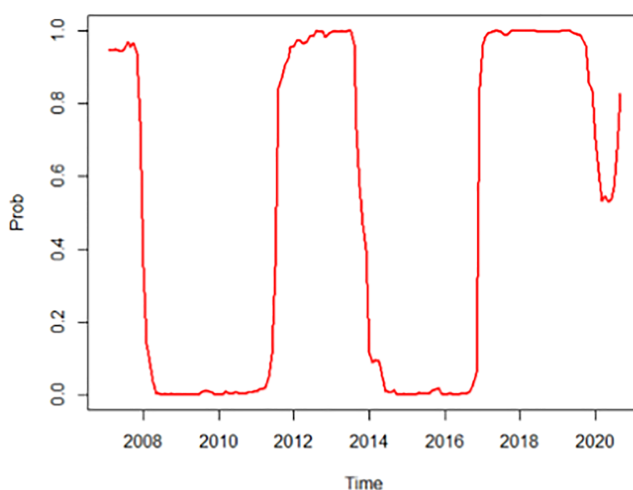
Furthermore, the analysis suggests that third-country exchange rates can influence the correlation between oil prices and local exchange rates. This finding is consistent with the concept of third-country effects in international trade and exchange rate dynamics (Frankel and Wei, 2007). When third-country exchange rates are incorporated into the analysis, a reduction in the co-movement between oil prices and local exchange rates is observed. This implies that the dynamics of third-country currencies, which may serve as vehicles for

international trade or financial transactions, can potentially mitigate or amplify the impact of oil price fluctuations on local exchange rates. Third-country currencies can influence the transmission of oil price fluctuations by affecting the competitiveness of oil-importing and oil-exporting countries. For example, exchange rate movements in major trading partners or global reserve currencies can amplify or dampen the impact of oil price changes on domestic exchange rates. This effect has implications for how oil prices interact with exchange rates in the sample countries, potentially altering the degree of pass-through depending on the currency structure of oil trade.

In Figure 2, we present the smoothed probabilities of being in the normal regime at various points in time  $\Pr(S_t = 2 | S_{t-1})$ . It is evident that during the period of 2008–2010, an abnormal state prevailed, with low probabilities indicating a low dependence on oil and exchange rates of importing countries. This aligns with the onset of the U.S. financial crisis during that time. A similar pattern emerged from 2014 to 2016, corresponding to one of the recent most significant oil price declines. The 70% drop in oil prices during this period was among the largest since World War II and the longest-lasting since the supply-driven collapse of 1986. These observations suggest a correlation between these low-dependence regimes and financial crises.

The explanation for this phenomenon lies in the fact that financial crises tend to disrupt the typical correlation between oil prices and exchange rates. This disruption arises from increased uncertainty and the alteration of established relationships between these variables during crises. A more pronounced correlation between oil prices and exchange rates exists in normal economic conditions due to stable economic factors. However, during crises, factors such as a flight to safety, demand and supply shocks, central bank interventions, and market sentiment can lead to a breakdown in this usual relationship. This divergence results from the unique dynamics of crisis periods. Our findings align with the research of [Pastpipatkul et al. \(2016\)](#) and [Beckmann et al. \(2020\)](#).

To ensure the validity of our MS-R-Vine model, we conducted a performance comparison with both the single-regime Vine copula and other Vine structures, specifically the C-D Vine copula. The results presented in Table 8 demonstrate that MS-R-Vine exhibits the lowest AIC (Akaike Information Criterion), signifying superior performance compared to other models, including the single-regime Vine copula. This outcome strongly suggests the presence of structural changes within the data.



Source(s): Author's calculations based on using R program

Figure 2. Smoothed probabilities of normal regime (high dependence)

**Table 8.** One-regime vs two-regime Vine Copula models

	C-Vine	MS-C-Vine	D-Vine	MS-D-Vine	R-Vine	MS-R-Vine
AIC	−150.741	−152.500	−152.606	−153.827	−155.115	−156.025

**Source(s):** Author’s calculations based on using R program

**5. Conclusion**

This study introduces a new approach to examining the relationship between oil prices and exchange rates by utilizing a regime-switching vine copula method. Unlike previous studies, which primarily focused on the direct effects of oil prices on exchange rates without considering structural changes, we apply the Markov-switching R-vine copula (MS-R-Vine) model. This advanced model allows us to capture the dynamic relationship between real oil prices and real exchange rates, specifically in five oil-importing countries. What makes our research unique is its focus on regime-switching and multivariate copula modeling, an area that has not been thoroughly explored in the context of oil price-exchange rate dynamics. By incorporating the MS-R-Vine model, we introduce a new lens through which these economic variables can be studied, particularly in the context of large oil-importing nations. This method allows us to account for structural changes, something previous studies have overlooked. Our study fills a crucial gap by offering insights into how the relationship between oil prices and exchange rates evolves over time, especially in response to different regimes or market conditions. The findings not only advance academic understanding but also provide practical implications for policymakers dealing with fluctuating oil prices and exchange rate volatility. Through this regime-switching approach, we provide a more nuanced view of these economic interactions, contributing to both theoretical development and informed policy decisions.

Our analysis unveils a pervasive negative correlation between oil prices and exchange rates across multiple currency pairs, particularly pronounced in oil-importing nations. This inverse relationship implies that surges in oil prices often coincide with a weakening of local currencies. Such currency devaluation can be attributed to the accompanying repercussions of elevated costs, trade deficits, and inflationary pressures stemming from higher energy import bills. Furthermore, our study delineates distinct variations in the correlation across two identified economic regimes. Regime 1 exhibits a relatively lower correlation between oil prices and exchange rates, indicative of a period characterized by low dependence or abnormal conditions. Conversely, regime 2 demonstrates a stronger negative correlation, representing a state of high dependence or more typical economic circumstances. Notably, the incorporation of third-country exchange rates into our analysis underscores their capacity to influence the correlation between oil prices and local exchange rates. This finding highlights the intricate global dynamics at play, where the movements of major international currencies can either amplify or mitigate the impact of oil price fluctuations on domestic exchange rates.

In light of these findings, we recommend a multifaceted approach to effectively navigate the complex interplay between energy markets and currency fluctuations within the global economic landscape. Firstly, robust exchange rate risk management strategies should be implemented to insulate against potential currency volatility arising from oil price shocks. Secondly, heightened awareness and monitoring of economic regime shifts are crucial, as the degree of dependence between oil prices and exchange rates can vary substantially across different economic conditions. Thirdly, enhanced global economic collaboration and coordination are imperative to promote stability and mitigate the ripple effects of energy market disruptions on currency markets. Additionally, diversification strategies aimed at reducing overdependence on oil imports should be pursued, particularly for nations heavily reliant on energy imports. Finally, continual monitoring and analysis of third-country exchange rate movements are essential, as these can indirectly influence the relationship between oil prices and domestic currencies.

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