
Uncovering the Dynamic Relationship Between Exchange Rates and Oil Price Volatility

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Abstract:

Purpose: The primary aim of this study is to address a gap in existing literature by providing a comprehensive analysis of prior research and developing a structured literature review. This approach seeks to enhance understanding of the topic by offering a clear and contextualized perspective on the relationship between crude oil prices and exchange rates.

Design/Methodology/Approach: Using daily data spanning from January 2020 to June 2023, this study investigates the interconnectedness between crude oil prices and exchange rates. As a first step, the impulse response function is employed to capture the dynamic interactions between the variables following a shock to either series. In the second step, a VAR-DCC-GARCH model is applied to analyze time-varying correlations and volatility dynamics between the two variables.

Findings: The results indicate that shocks in crude oil prices have a direct and significant impact on exchange rate volatility. Furthermore, the VAR-DCC-GARCH analysis reveals a strong dependency of the Japanese yen, Mexican peso, Canadian dollar, and Indian rupee on oil price volatility. In contrast, the Russian ruble demonstrates relative resistance to fluctuations in crude oil prices.

Practical Implications: The findings suggest that the dollarization of the global economy plays a significant role in shaping the relationship between foreign exchange markets and crude oil price volatility, with important implications for policymakers and international investors.

Originality/Value: This study contributes to existing literature by combining impulse response analysis with a VAR-DCC-GARCH framework to provide a comprehensive and dynamic assessment of the relationship between oil prices and exchange rates across major economies.

Keywords: Crude oil price, exchange rate, volatility, impulse response function, VAR-DCC-GARCH.

JEL Codes: Q43, F31, B23.

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1. Introduction

Within the framework of international trade, the US dollar has emerged as the dominant currency for transactions involving key commodities such as energy products and precious metals. The role of the dollar in the energy sector has been extensively examined using various empirical approaches. In recent academic discussions, this relationship is often analysed through the interaction between exchange rates and fluctuations in crude oil prices, particularly West Texas Intermediate (WTI).

WTI is one of the most important benchmarks in the global energy market, with substantial trading volumes daily. The interconnectedness between countries involved in crude oil trade—whether as importers or exporters—is largely facilitated through the US dollar, which has become the primary currency in international trade. This strong linkage between the energy sector and the dollar is commonly referred to as the “petrodollar” system and has significant implications for major global currencies such as the British pound (GBP), the euro, and the Japanese yen.

The international crude oil market can be broadly viewed through two channels: the WTI market and the financial transmission mechanism (FEM). According to Krugman (1983), if an economy relies heavily on oil in its tradable sector, an increase in oil prices may lead to a depreciation of the domestic currency. Furthermore, the FEM reflects how wealth is redistributed globally, as rising oil prices tend to transfer wealth from oil-importing countries to oil-exporting countries.

From a theoretical perspective, Bloomberg and Harris (1995) argue that if oil is a homogeneous, globally traded commodity priced in US dollars, a depreciation of the dollar should lead to lower oil prices. However, more recent studies, such as Umar *et al.* (2023), suggest that this relationship has evolved. The financialization of crude oil markets—driven by the expansion of financial instruments such as futures and derivatives—has significantly altered market dynamics. Speculative activities in these markets can amplify price volatility and influence exchange rates beyond traditional supply and demand factors.

Similarly, Kilian (2009) emphasizes the importance of distinguishing between demand-driven, supply-driven, and speculative shocks in oil prices to better understand their complex and often non-linear relationship with exchange rates. Wang *et al.* (2023) further highlight that, with increasing globalization and financialization, WTI has become an integral component of many investment portfolios. As a result, currencies that are closely linked to oil trading are likely to experience significant spillover effects.

The first contribution of this study is to address a gap in the literature by providing a comprehensive and structured review of existing research, offering a clearer and

more contextualized understanding of the relationship between oil prices and exchange rates.

The second contribution lies in the use of high-frequency data, which enables a more detailed analysis of the interaction between oil price fluctuations and currency markets. Specifically, this study examines the relationship between WTI and four major currencies: the Mexican peso, the Canadian dollar, the Indian rupee, and the Japanese yen. The analysis is based on daily data covering the period from January 1, 2020, to October 8, 2023.

The remainder of the paper is organized as follows: Section 2 reviews the relevant literature; Section 3 describes the data and empirical methodology; Section 4 presents the results; and Section 5 concludes with policy implications.

2. Literature Review

The existing literature highlights a strong interconnection between oil markets and foreign exchange markets, with each study offering distinct findings depending on the methodologies employed and the sample periods considered. Examining the impact of oil price movements on exchange rates reveals several important dynamics. For instance, demand- and risk-driven oil price shocks are found to significantly contribute to exchange rate fluctuations (Malik and Umar, 2019), whereas supply-side shocks tend to have a more limited or insignificant effect (Xu *et al.*, 2019).

From a different perspective, Jiang *et al.* (2020) show that both oil supply shocks and oil-specific demand shocks exert negative and asymmetric effects on exchange rates. Similarly, Chkir *et al.* (2020) identify a strong linkage between oil prices and exchange rates across selected economies over the period 1990–2017.

However, during major global crises such as the COVID-19 pandemic and the Russia–Ukraine conflict, Kyriazis and Corbet (2024) find that the influence of major currencies on Latin American exchange rates weakened. In this context, currencies such as the Argentinian and Uruguayan pesos primarily absorbed shocks, while the Brazilian real and Peruvian sol acted as key transmitters of spillover effects.

Over the period 2008–2020, Asadi *et al.* (2022) report generally low levels of interconnectedness between energy and currency markets. In contrast, earlier evidence from 2000–2015 by Huang *et al.* (2017) shows that the oil–exchange rate relationship varies across countries: a depreciation in the exchange rate weakens the oil–stock relationship in China but strengthens it in Russia. A wide range of methodologies has been employed to examine the interaction between the US dollar and crude oil prices (Atems *et al.*, 2015; Jammazi *et al.*, 2015; Ji *et al.*, 2018; Bilal *et al.*, 2025), reflecting the central role of the dollar as the primary invoicing currency in global oil trade.

Given this dominance, fluctuations in exchange rates against the US dollar are considered a key factor influencing crude oil price dynamics. In line with this perspective, the present study focuses on the impact of foreign exchange rate volatility on crude oil prices. The findings indicate a significant dependency relationship between exchange rates and the oil market over the period under analysis.

3. Data and Methods

To examine the impact of crude oil price volatility on exchange rates, this study focuses on a selection of currencies that are closely linked to the global energy sector. Specifically, five currencies are considered: the Mexican peso, the Japanese yen, the Russian ruble, the Chinese yuan, and the Australian dollar. These currencies are chosen due to their strong economic ties to crude oil markets, either as major producers, exporters, or importers.

The analysis is conducted in two stages. In the first stage, the impulse response function is employed to assess the dynamic interaction between crude oil price shocks and exchange rates. Using daily data allows for a detailed examination of these relationships under varying market conditions.

Country-specific characteristics play an important role in shaping these dynamics. The Mexican economy is highly dependent on the energy sector, making its currency particularly sensitive to oil price fluctuations. The Australian economy, while resource-rich and diversified, exhibits more complex responses to oil price shocks, reflecting its broader economic structure and trade linkages. Japan, as a major oil importer, shows strong responsiveness of the yen to changes in oil prices.

In contrast, Russia, as a leading oil exporter, presents a distinct case where exchange rate dynamics are closely tied to both oil price movements and broader geopolitical and trade considerations. Meanwhile, China, as both a significant importer and exporter of crude oil, demonstrates a strong connection between its currency and the US dollar within the context of global energy trade.

In the second stage, a VAR-DCC-GARCH model is applied to capture time-varying correlations and volatility spillovers between crude oil prices and exchange rates. This combined approach highlights the differential impact of oil price volatility across the selected currencies and provides insights into the interconnectedness of currency markets in response to energy-related shocks.

The empirical analysis is based on daily data spanning from January 1, 2020, to October 8, 2023. This period is characterized by significant global disruptions, including the COVID-19 pandemic and geopolitical tensions such as the Russia–Ukraine conflict, which have had substantial effects on both energy and financial markets.

Table 1. Descriptive Data

Data	Description
Energy	Crude oil price in US \$ per barrel
Mexican	Mexican peso to US \$
Japanese yen	Japanese yen to US \$
Russian	Russian rubble to US \$
Chinese	Chinese yuan to US \$
Australian	Australian dollar to US \$

Source: Own study.

Table 2. Summary Statistics

	Crude oil	USD/Japane se Yen	USD/Mexican Pesos	USD/Canadia n Dollar	USD/Indian Rupee	USD/Russia n Rubble
Mean	72.35074	118.6943	20.28068	1.305822	76.49582	73.04935
Median	74.49000	111.4400	20.10270	1.301000	75.13100	73.66030
Maximum	133.1800	150.3200	25.11300	1.462200	83.03700	143.0000
Minimum	9.120000	102.8300	17.08000	1.203900	70.80800	51.45000
Std. Dev.	24.96555	13.60424	1.454220	0.049583	3.529688	9.239425
Skewness	-0.056550	0.651157	0.658737	0.264079	0.620975	1.446933
Kurtosis	2.580234	1.889411	4.135947	2.409354	1.983891	10.34939
Jarque-Bera	7.173937	111.1962	114.8662	23.83080	97.73954	2511.115
Probability	0.027682	0.000000	0.000000	0.000007	0.000000	0.000000

Source: Own study.

3.1 Impulse Response between the Exchange Rate and the Oil Price

To appropriately support the design of the analytical framework capturing the co-movement between crude oil prices and exchange rates, this study aims to provide a renewed perspective on currency markets, where energy commodities—particularly crude oil—play a catalytic role alongside other key commodities in shaping the international monetary system. The analysis begins by examining the causal interactions between these variables.

For this purpose, impulse response functions (IRFs) are derived from a Bayesian Vector Autoregression (BVAR) framework. These IRFs trace the dynamic effects of a one-standard-deviation shock, identified through Cholesky decomposition, on each variable in the system. A lag length of 10 periods is selected for the BVAR model. The IRFs are computed by first simulating the model over 100 periods with zero shocks, followed by the introduction of a single shock, allowing the system to gradually return to its stochastic steady state.

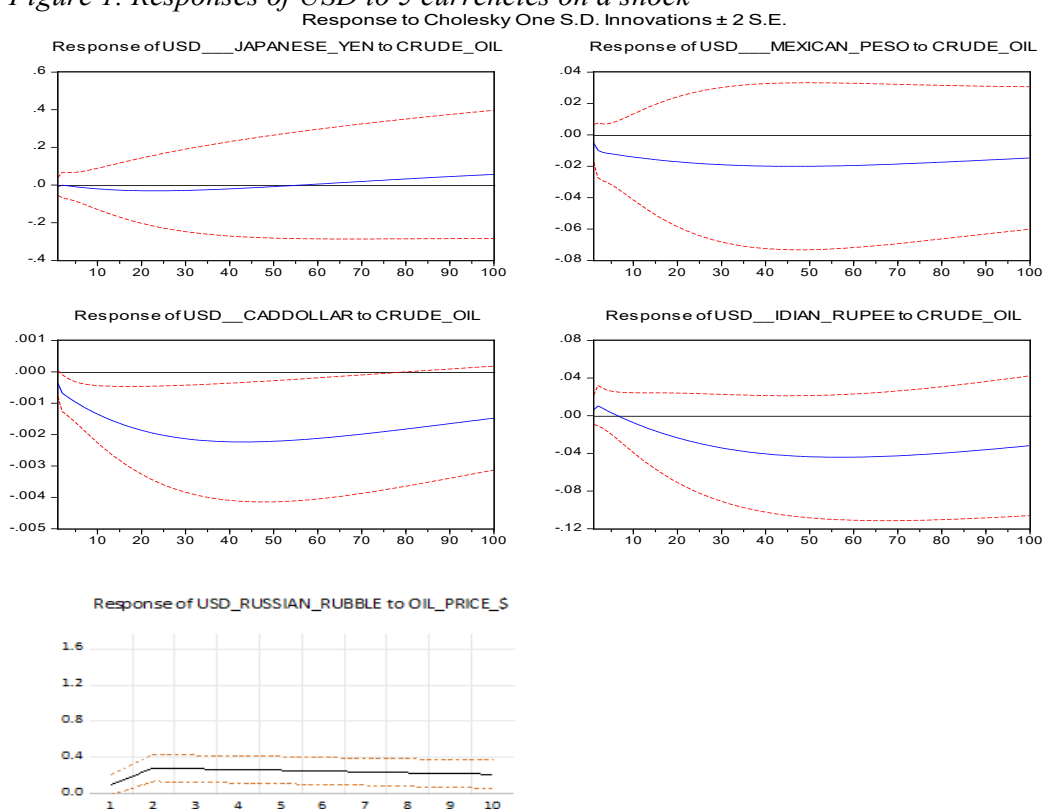
Figure 1 presents the accumulated impulse responses of exchange rates to a shock in crude oil prices. The analysis includes crude oil prices and the exchange rates of USD against the Japanese yen, Mexican peso, Canadian dollar, and Indian rupee. The results provide clear evidence that exchange rates

respond significantly to shocks in crude oil prices, indicating the presence of strong causal interactions.

The findings reveal an inverse relationship between crude oil prices and the exchange rates of the Mexican peso, Canadian dollar, and Indian rupee over the examined horizons. Specifically, a positive one-standard-deviation shock in crude oil prices leads to a decline in these exchange rates, with the effect gradually diminishing over time as the system converges toward equilibrium. Conversely, a positive shock in these currencies tends to exert downward pressure on crude oil prices, with the effect intensifying before stabilizing.

In contrast, the USD/JPY exchange rate exhibits a response pattern that closely aligns with that of crude oil prices, indicating a more synchronized dynamic between the two variables. Overall, these results confirm the suitability of the proposed modeling framework for capturing the complex interactions between crude oil prices and exchange rates and highlight the existence of differentiated responses across currencies within the international monetary system.

Figure 1. Responses of USD to 5 currencies on a shock



Source: Own study.

3.2 VAR-DCC- GARCH Estimator

The Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model is widely used in the literature to analyse volatility dynamics (Bollerslev, 1986), building on the earlier Autoregressive Conditional Heteroskedasticity (ARCH) framework introduced by Engle (1982). While the ARCH model provides a useful approach for modelling time-varying variance, it often requires the specification of a relatively large number of lags and may encounter limitations in capturing persistent volatility patterns.

To address these issues, the GARCH model was developed as an extension of the ARCH framework, allowing for a more flexible lag structure and a more parsimonious representation of volatility dynamics. In particular, the GARCH process incorporates both past squared residuals and past conditional variances, thereby capturing the persistence and clustering commonly observed in financial time series. The standard GARCH model, as introduced by Bollerslev (1986), is defined as follows:

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1} \quad \alpha_0 > 0 \quad \alpha_1 > 0 \quad \beta_1 > 0$$

For GARCH model a process for sufficient condition for existence of the 2mth moment is:

$$\mu(\alpha_1, \beta_1, m) = \sum_{j=0}^m \binom{m}{j} \alpha_1^j \beta_1^{m-j} < 1$$

where:

$$\alpha_0 = 1, \quad \alpha_j = \prod_{i=1}^j (2i - 1), \quad j = 1 \dots$$

The 2mth moment can be expressed by the recursive formula:

$$E(\varepsilon_t^{2m}) = \alpha_m \left[\sum_{n=0}^{m-1} \alpha_n^{-1} E(\varepsilon_t^{2n}) \alpha_0^{m-n} \binom{m}{m-n} \mu(\alpha_1, \beta_1, n) \right] \\ * [1 - \mu(\alpha_1, \beta_1, m)]$$

The process for mean lag in the conditional variance equation is given by:

$$\zeta = \sum_{i=1}^{\infty} i \delta_i / \sum_{i=1}^{\infty} \delta_i = (1 - \beta_1)^{-1}$$

And the median lag is found to be:

$$v = -\log 2 / \log \beta_1$$

$$\text{If } 3\alpha_1^2 + 2\alpha_1\beta_1 + \beta_1^2 < 1 \quad E(\varepsilon_t^2) = \alpha_0(1 - \alpha_1 - \beta_1)^{-1}$$

And

$$E(\varepsilon_t^4) = 3\alpha_0^2(1 + \alpha_1 + \beta_1)[(1 - \alpha_1 - \beta_1)(1 - \beta_1^2 - 2\alpha_1\beta_1 - 3\alpha_1^2)]^{-1}$$

The coefficient of the kurtosis is therefore:

$$\begin{aligned} k &= \left(E(\varepsilon_t^4) - 3E(\varepsilon_t^2)^2 \right) E(\varepsilon_t^2)^{-1} \\ &= 6\alpha_1^2(1 - \beta_1^2 - 2\alpha_1\beta_1 - 3\alpha_1^2)^{-1} \end{aligned}$$

The GARCH framework is widely regarded as an appropriate model for capturing the volatility dynamics of financial and commodity markets. In this study, a Dynamic Conditional Correlation GARCH (DCC-GARCH) model is employed to estimate the time-varying volatility of crude oil prices and exchange rates. To account for cross-correlations and autocorrelations, returns are first modelled using a Vector Autoregression (VAR) specification with one lag. The combined VAR-DCC-GARCH approach allows for the estimation of both return and volatility spillovers between the variables.

The VAR-DCC-GARCH model, as proposed by Engle (2002), serves as a standard benchmark for estimating time-varying variances and covariances. Within this framework, the conditional correlation between multiple zero-mean random variables is defined as follows:

$$\rho_{i,j,t} = \frac{\sum_{s=1}^{t-1} \lambda^s \varepsilon_{i,t-s} \varepsilon_{j,t-s}}{\sqrt{\left(\sum_{s=1}^{t-1} \lambda^s \varepsilon_{i,t-s}^2 \right) \left(\sum_{s=1}^{t-1} \lambda^s \varepsilon_{j,t-s}^2 \right)}} = [R_t]_{ij}$$

In a multivariate context, the same λ must be used for all assets to ensure a positive definite correlation matrix. According to (Engle, 2002) risk metrics uses the value of .94 for λ on all the exchange rate and the crude oil prices.

The conditional covariance matrix of returns is defining as follow:

$$E_{t-1}(r_t r_t') \equiv H_t$$

The estimators can be expressed in matrix notation respectively:

$$H_t = \frac{1}{n} \sum_{j=1}^n (r_{t-j} r'_{t-j}) \quad \text{and} \quad H_t = \lambda (r_{t-1} r'_{t-1}) + (1 - \lambda) H_{t-1}$$

Within the GARCH model, the full covariance matrix is constructed by assuming the conditional correlations are all zero. More precisely,

$y_t = Ar_t$, $E(y_t y'_t) \equiv V$ is diagonal. By assuming that $V_t = E(y_t y'_t)$ then,

$H_t = A^{-1} V_t A^{-1}$. The multivariate GARCH models are generalisation or modelling. (Bollerslev, 1986). The VAR-DCC-GARCH model is:

$$H_t = D_t R D_t \quad \text{where} \quad D_t = \text{diag}\{\sqrt{h_{i,t}}\}$$

Where R is a correlation matrix containing the conditional correlations, as can directly be seen from rewriting this equation as:

$$E_{t-1}(\varepsilon_t \varepsilon'_t) = D_t^{-1} H_t D_t^{-1} = R \quad \text{since} \quad \varepsilon_t = D_t^{-1}$$

The estimation formula of the VAR-DCC-GARCH model and the mean equation is as follow:

$$R_t = \mu + \phi R_{t-1} + e_t \text{ with } e_t = D_t^{1/2} \eta_t$$

3.3 Econometric Estimation Methodology

As noted earlier, the GARCH estimator is widely used in the literature to model volatility dynamics (Bollerslev, 1986), building on the ARCH framework introduced by Engle (1982). While the ARCH model provides a useful approach for capturing time-varying variance, its empirical application often requires the imposition of a fixed lag structure and may face limitations in adequately capturing persistence in volatility. To address these shortcomings, extensions of the ARCH class, such as the GARCH model, were developed to allow for longer memory and a more flexible lag structure.

A variety of GARCH-type models have been proposed to analyse volatility that evolves over time and across different markets or asset classes. In this study, we employ a VAR-DCC-GARCH framework to model the joint dynamics of crude oil prices and exchange rates.

The VAR component enables the analysis of how these variables evolve jointly over the sample period, capturing their interdependencies in mean dynamics. The DCC-GARCH component, in turn, models the time-varying volatility and conditional correlations between the series.

Before introducing the DCC-GARCH specification, we first present the VAR model for crude oil prices and exchange rates.

VAR Model:

The measurement of volatility and interdependence begins with a Vector Autoregression (VAR) framework, which captures the dynamic interactions between oil prices and exchange rates in terms of both magnitude and persistence. The VAR model used in this study is specified as follows:

$$Y_t = A_0 + \sum_{i=1}^P A_t Y_{t-i} + \varepsilon_t$$

$$Y_t = [\ln(O_t/O_{t-1}), \ln(E_t/E_{t-1})]'$$

$$Y_{Ot} = A_1 + \mu_{1,1}^O Y_{O(t-1)} + \mu_{1,2}^O Y_{O(t-2)} + \dots + \mu_{1,p}^O Y_{O(t-T)} + \mu_{1,1}^E Y_{E(t-1)} + \mu_{1,2}^E Y_{E(t-2)} + \dots + \mu_{1,k}^E Y_{E(t-T)} + \varepsilon_O$$

$$Y_{Et} = A_2 + \mu_{2,1}^E Y_{E(t-1)} + \mu_{2,2}^E Y_{E(t-2)} + \dots + \mu_{2,k}^E Y_{E(t-T)} + \mu_{2,1}^O Y_{O(t-1)} + \mu_{2,2}^O Y_{O(t-2)} + \dots + \mu_{2,p}^O Y_{O(t-T)} + \varepsilon_O$$

P is the number of currencies, k is the number of oil price, T is the time-period of the study.

E_t is the price of the exchange rate in the period t, O_t is the price of oil in the period t, A_t is 2×2 parameter matrix of lagged variables, $\varepsilon_t = [\varepsilon_{1,t}, \varepsilon_{2,t}]'$,

$$E(\varepsilon_t) = 0, \quad E(\varepsilon_t \varepsilon_t') = \sigma^2, \quad E(\varepsilon_t \varepsilon_s') = 0, \quad t \neq s$$

As an efficient causal analysis method, impulse response function can be used to analyse the relationship between variables. Residual in VAR model reflects the impact from external system on system variables, the coefficient matrix in the moving average form, is also impulse response coefficient matrix as follow:

$$F_t = C_0 + B_0 \varepsilon_t' + B_1 \varepsilon_{t-1}' + \dots + B_n \varepsilon_{t-n}' + \dots$$

Where $F_t = [f_{1,t}, f_{2,t}]'$ and $B_n = [b_{ij,n}]$ are 2×2 coefficient matrixes, $b_{ij,n}$ reflects the impact of $f_{i,t-n}$ on $f_{j,t}$ during the period of $t-n$. Therefore, the accumulative response of $f_{i,t}$ to $f_{j,t}$ is written as follow:

$$\sum_{t=0}^m b_{ij,t}$$

VAR-DCC-Model:

The DCC GARCH is introduced to solve this problem. The number f parameters to be estimated in the model increases linearly and not exponentially, which make this model deal the dimension and duration. The model decomposes the matrix H_t where H_t is triangular matrix representing the conditional variance –covariance matrix.

$$H_t = \begin{pmatrix} h_{11,t} & h_{12,t} \\ h_{21,t} & h_{22,t} \end{pmatrix}$$

The model composes the matrix H_t as follows: $H_t = D_t R_t D_t$, $e_t | \Psi_{t-1} \sim N(0, H_t)$, e_t is the residual vector composed by the residues of all the markets, Ψ_{t-1} is the market information available at time $t-1$, H_t is the dynamic condition covariance matrix, D_t represent the diagonal matrix of time varying standard deviation of multivariate GARCH model with all three categories of volatiles variables returns, with $(\sigma_{i,t}^2)^{1/2}$ on i th diagonal.

$$D_t = \begin{bmatrix} \sqrt{\sigma_{E,t}^2} & 0 \\ 0 & \sqrt{\sigma_{O,t}^2} \end{bmatrix}$$

$$R_t = \begin{bmatrix} \varepsilon_{CC,t} & \varepsilon_{CS,t} \\ \varepsilon_{SC,t} & \varepsilon_{SS,t} \end{bmatrix} = \begin{bmatrix} 1 & \varepsilon_{CS,t} \\ \varepsilon_{SC,t} & 1 \end{bmatrix}$$

R has to definite positive and all the parameters should be equal to or less than one.

In order to fulfil this condition, R_t has been modelled as follow:

$$R_t = \text{diag}(Q_{E \ O,t})^* Q_{E \ O,t} \text{diag}(Q_{E \ O,t})^*$$

$Q_{E \ O,t} = (q_{pkt})$ is a symmetric positive define matrix. $Q_{E \ O,t}$ is assumed to vary according to a GARCH process:

$$Q_{E \ O,t} = (1 - \theta_1 - \theta_2)Q^* + \theta_1(\varepsilon_{E,t-1}\varepsilon_{O,t-1}) + \theta_2(Q_{E \ O,t-1}) + \theta_3(Q_{E \ O,t-1})$$

θ_1 , θ_2 and θ_3 are scalar parameters to capture the effects of the previous shocks and previous dynamic conditional correlation on current dynamic conditional correlation, are non-negative and satisfy $\theta_1 + \theta_2 < 1$. $Q_{E O,t}$ is the unconditional variance between series k and p and follows a GARCH process, Q^* is the unconditional covariance between the series estimated in step 1. The parameters θ_1 and θ_2 are estimated by maximising the log-likelihood function. The log likelihood function is expressed as follow:

$$L(\theta) = -\frac{1}{2} \sum_{t=1}^T (k \log(2\pi)) + 2 \log([D_t]) + \log([R_t]) + \varepsilon_t' R_t^{-1} \varepsilon_t$$

The modified model of (Cappiello et al., 2006) for incorporating the asymmetrical effect Allow the studied model VAR-DCC-GARCH to be written as follow:

$$Y_t = A_0 + \sum_{i=1}^P A_i Y_{t-i} + \varepsilon_t$$

$$H_t = D_t R_t D_t$$

$$R_t = \text{diag}(Q_{E O,t})^* Q_{E O,t} \text{diag}(Q_{E O,t})^*$$

$$Q_{E O,t} = (1 - \theta_1 - \theta_2) Q^* + \theta_1 (\varepsilon_{E,t-1} \varepsilon_{O,t-1}) + \theta_2 (Q_{E O,t-1}) + \theta_3 (Q_{EO,t-1})$$

4. Results

The fundings of the VAR-DCC-GARCH model is displayed within the graphics analysed below within this section and considering the specification of the model in the previous description for the studied sample within the selected period.

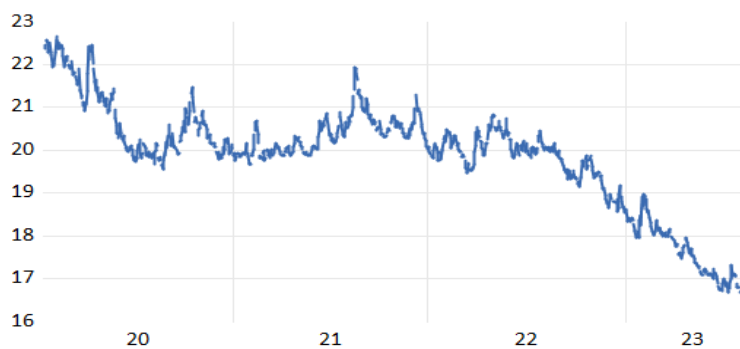
Graph 1. DDC Conditional correlation between Japanese yen exchange rate and oil price



Source: Own study.

Japan is one of the largest importers of crude oil, relying heavily on supplies from the Middle East. This dependency has become more pronounced in recent years, particularly due to significant fluctuations in the Japanese yen against the US dollar, especially in the early years of the study period following the COVID-19 crisis. The reliance on the US dollar for international transactions contributes to a strong relationship between the exchange rate and crude oil price volatility. As a result, the dollarization of these transactions reinforces the sensitivity of the yen to changes in global oil price dynamics.

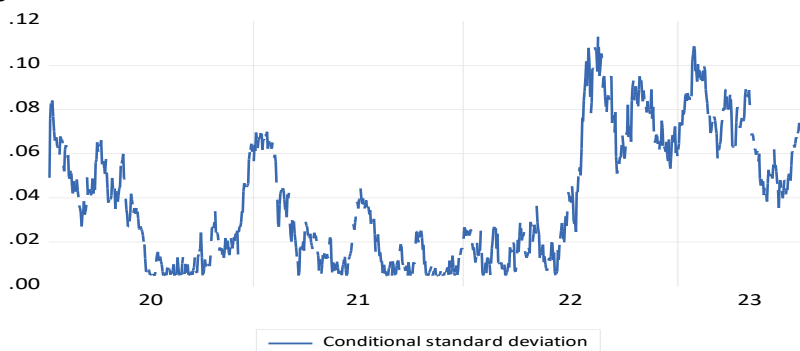
Graph 2. DDC Conditional correlation between Mexican peso exchange rate and oil price



Source: Own study.

Mexico is among the world's largest producers of crude oil. Despite being a significant producer, the country relies on the US dollar for its imports, creating a strong link between crude oil price volatility and the exchange rate. Mexico's economic system is closely tied to that of the United States, which helps explain why crude oil exports are denominated in US dollars. As a result, the dollarization of Mexico's economy leads to a strong dependence of the exchange rate on fluctuations in crude oil prices.

Graph 3. DDC Conditional correlation between Canadian dollar exchange rate and oil price

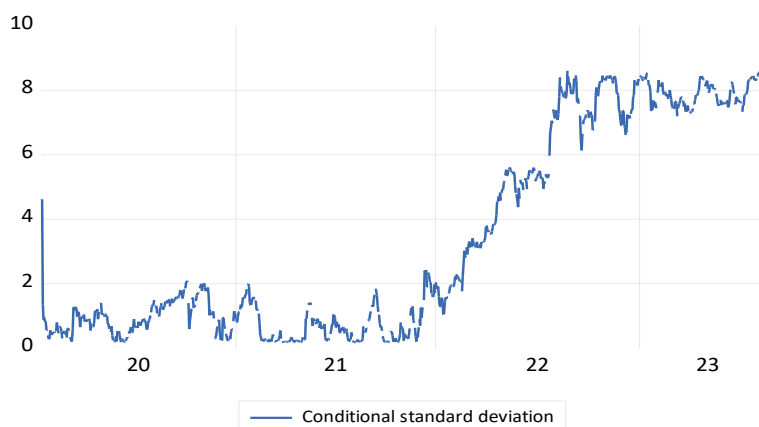


Source: Own study

The Canadian dollar appears relatively less influential compared to the other foreign exchange markets examined in this study. The observed trend indicates that, from 2020 to 2021, the Canadian dollar had a positive and relatively stable impact on oil price volatility. However, between 2022 and 2023, there is a notable increase in the correlation between oil prices and the Canadian dollar.

This increase can be attributed to changes in international trade policies implemented by Canada and the United States, which have enhanced the role of the Canadian dollar in global foreign exchange markets. Nevertheless, despite this growing influence, investors continue to show a stronger preference for the US dollar over the Canadian dollar in oil markets.

Graph 4. DDC Conditional correlation between Indian rupee exchange rate and oil price

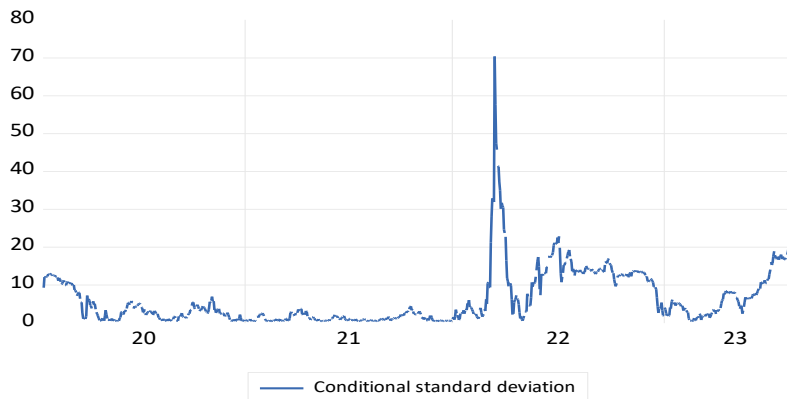


Source: Own study.

The Indian rupee exhibits a consistently positive correlation throughout 2020 and the first half of 2021. However, during the remainder of the study period, the rupee demonstrates a positive impact on oil price volatility. This suggests that, in the latter part of the period, investors showed a stronger preference for the US dollar over the rupee in the oil market. This behaviour can be interpreted as evidence that the Indian market is largely dollarized in crude oil transactions.

India is recognized as the second-largest importer of crude oil after China. This further confirms that the global crude oil market primarily operates in US dollars rather than in rupees, making the Indian rupee highly sensitive to fluctuations in oil price volatility.

Graph 5. DDC Conditional correlation between Russian rubble exchange rate and oil price



Source: Own study.

Russia is one of the world's largest exporters of crude oil. In its export operations, Russia has increasingly utilized its national currency, the Russian ruble, which helps explain the relatively limited influence of the US dollar on its dependence on the oil market. During the period under study, the degree of dollarization in Russia's foreign exchange market appears to be less pronounced, partly due to its evolving economic and geopolitical relationship with the United States in the energy sector.

The global crude oil market is largely driven by major oil-producing countries and the volatility of prices. This may explain why Russia's exchange rate dynamics are not strongly linked to the US dollar in the context of oil transactions but are instead more directly influenced by fluctuations in crude oil prices, given its role as a major producer.

5. Conclusion and Policy Implications

Following recent shifts in international trade policies, the oil market has become increasingly influenced by the scale and dynamics of the global economy. Examining the impact of foreign exchange rate volatility on oil markets highlights the importance of dollarization within the global economic system. In this study, five currencies are analysed—the Japanese yen, the Mexican peso, the Canadian dollar, the Indian rupee, and the Russian ruble—over the period from 2020 to 2023.

The existing literature suggests that exchange rate dynamics are often interconnected through the process of dollarization in international markets. The strength and validity of this relationship depend largely on a country's role in the oil market, whether as a major producer or importer. This creates an important question regarding the factors that link exchange rate volatility to oil price fluctuations.

This study focuses on how foreign exchange rates are influenced by oil price volatility. The dollarization of the global economy implies that the US dollar plays a significant role in driving exchange rate movements. This effect is evident across most of the currencies examined, except for the Russian ruble, which remains less influenced due to its use in domestic and certain external oil transactions.

The findings indicate significant interconnectedness between oil price volatility and the Japanese yen, Canadian dollar, Mexican peso, and Indian rupee. In contrast, the exchange rate of the Russian ruble against the US dollar does not exhibit a strong relationship with oil price volatility. These results offer meaningful insights and potential policy implications at the international level.

Finally, the widespread dollarization of the global economy may serve as a stabilizing mechanism in the context of oil price volatility. By anchoring transactions in a dominant currency, it can contribute to greater stability in the global business cycle and help maintain more consistent price levels, thereby supporting more controlled global inflation dynamics.

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