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# Petroleum Output, Policy Uncertainty and Exchange Rates of Currencies of 3 Largest Crude Oil Producing Countries

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***Abstract:*** This research evaluates currency return effects of crude oil output and macroeconomic policy uncertainty in 3 oil producing countries. The DCC-GARCH model and the MS(2)-VAR(2) were estimated for the 3 different countries. According to the research findings, the dynamic effect of uncertainty on petroleum production was negative and significant in all countries for both Regime 1 (low turbulence) and Regime 2 (high turbulence). We found substantial negative returns effects of policy uncertainty in the 3 countries. Only in the case of Russia, we had negative nexus between petroleum output growth and returns on the rubble for both Regime 1 and Regime 2 respectively. In the United States; there is a long duration of stay (83.729%), in the low turbulent period as against staying in the highly turbulent period; and the probability of transiting from the low turbulent period to the tremendously turbulent period is lower (26.849%) as against 39.453%. In Saudi Arabia, the duration of stay (96.53%) in the low turbulent period exceeds the duration of stay in the highly volatile period. In Russia, we found a long duration of stay in the highly turbulent period; and there is a high probability of transition from the low turbulent period to the tremendously turbulent period is higher (29.7%). The findings of this study are significant for executing stabilization plans regarding energy prices, exchange rates and evaluating regulatory measures to rectify macroeconomic disparities.

***Keywords***: Crude oil production, economic policy uncertainty, currency return, regime 1 & 2, Markov-Switching VAR model, transition probability

***JEL classification***: A20, B34, D26

## 1. Introduction

The worldwide operations of petroleum product exploration, extraction, refining, transportation, and marketing are together referred to as the petroleum industry. Fuel oil and gasoline (petrol) make up the industry's two biggest volume products. Due to the high levels of risk and uncertainty involved in oil and gas investments as well as the extremely unstable price levels, the petroleum industry's corporate framework is very different from other industries. The United States, Russia, and Saudi Arabia are the three largest oil-producing countries in the world. This is further disclosed in Table 1. In 2023, these nations collectively produced 32.8 million barrels of oil per day, approximately 40% of the world's aggregate. Russia was the country with the most crude oil production in 2017, but production growth in Russia has since lagged behind the United States. Russia's average yearly output peaked in 2019 at 10.8 million barrels per day, lagging behind the US by 1.4 million barrels per day. Russia was one of the OPEC$^{+}$ nations that declared production cuts in November 2022. It also confirmed supplementary voluntary cuts of 500,000 b/d in February 2023. According to EIA (2024) sanctions and corporations' actions in reaction to the full-scale attack on Ukraine are the main causes of the voluntary cuts that have all lowered production in Russia recently. However, actual production reductions seem to have been less severe than predicted; according to (IMF, 2023), Russia's production fell by just 200,000 b/d in 2023.

**Table 1: Oil Production by Country**

| *Country* | *Production of Oil Annually (Barrels per Day)* |
|---|---|
| United States | 14,837,639,510 |
| Saudi Arabia | 12,402,761,040 |
| Russia | 11,262,746,200 |

*Source:* U.S. Energy Information Administration (EIA) (2024)

For the past six years, the United States produced more crude oil than any other country, according to the International Energy Statistics (2024). In June of 2024, the United States produced 13214 BBL/D/1K of crude oil, up from 13189 BBL/D/1K in May of the same year. The United States has emerged as the world's leading producer of crude oil since 2023. The United States' oil output peaked in 2023 at 19.4 million barrels per day, the largest amount throughout the time under study. In December 2023, the average monthly output of crude oil in the United States reached a record high of almost 13.3 million barrels per day. The financial crisis-era spike in international oil prices, especially from OPEC nations, spurred the U.S. energy sector to boost domestic output.

As of 2016, the United States ranked eleventh in the world with verified oil reserves of 35,230,000,000 barrels. This explains for 2.1% of overall global oil reserves of 1,650,585,140,000 barrels. The COVID-19 pandemic's economic repercussions resulted in a decline in demand and prices in 2020 and 2021, marking a single exception to the trend of U.S. petroleum output growth since 2009. The rise in the nation's total production of natural gas and crude oil in recent years has been mostly driven by the Permian Basin. In 2022, the United

States produced 14.7% of the world's crude oil, while Saudi Arabia produced 13.1% and Russia produced 12.7%. Even though it leads the world in petroleum production, the United States still has 55,251 million barrels of reserves (WDI, 2022).

In 2023, Saudi Arabia produced 13.39 million barrels of oil per day, up from 12.19 million in 2022. Saudi Arabia gained two million barrels per day of production between 1998 and 2023, reaching a peak of 12.4 million barrels per day in 2016 (EIA, 2023). As stated by OECD (2023), in 2023, Saudi Arabia's mean monthly production reached its maximum at 10.6 million barrels per day, a figure that was 1.3 million barrels less than the US's in the same year. Following the OPEC+ cuts as well as discretionary cuts Saudi Arabia made to counteract sluggish demand, Saudi Arabia's crude oil production fell by 900,000 barrels per day in 2023. In light of Saudi Aramco's 12.0 million b/d production capacity plus extra 300,000 b/d from its portion of the Neutral Zone territory shared with Kuwait, output in Saudi Arabia was limited to what the United States could produce in 2023.

Business companies frequently take fluctuations in currency rates into account when making investment choices. Exchange rate volatility has long been a source of worry for economic managers due to its impact on firm cycles. This is to prevent exchange rate fluctuations, which may result in inefficiencies, from distorting the monetary authorities' objective of preserving price stability. According to Ghiba (2010), significant depreciation in the currency rate might jeopardize the banks' ability to stay solvent as well as the borrower's ability to repay debts. Most monetary models that influence exchange rates take interest rates into account. Nonetheless, it is impossible to downplay the significance of exchange rate volatility when analyzing the dynamics of interest rates. This implies that the differences between the two variables may be examined separately to see how endogenous and external factors influence them. Belke, Geisslreither, and Gros (2004) claim that the two variables may move in tandem because other factors, including as capital flows, country risks, and rates of money growth, may have an impact on their connection. The question of how the volatility of interest rates and currency rates co-move in developing nations has not, however, been thoroughly explored in the literature. This highlights even more how important the current study is.

In the language of economics, uncertainty is the absence of certainty in any process of decision-making or forecasting pertaining to economic variables. 'It may result from erratic occurrences, a dearth of trustworthy data, or intricate and unstable economic contexts. This idea is fundamental to behavioral economics because it influences how people and institutions make decisions when faced with risk or uncertainty. Risk and uncertainty are related but separate ideas in this context. When possible outcomes and their probability are known, a situation is said to be in risk; when these probabilities are unknown, it is said to be in uncertainty. To completely realize the scope of the idea of uncertainty in economics, one must comprehend the link between risk and uncertainty. A foreign exchange market is a venue for the trading of foreign currencies. The primary players in the foreign exchange market are bureau de change (BDC), merchant, commercial, and central banks. The central bank is a wholesaler, whereas the other banks and BDC are retail sellers. The cost of exchanging one currency for another on the foreign exchange market is known as the exchange rate. One of the most important price variables in an economy is the exchange rate. It contributes to maintaining the value of a home currency abroad. Economic managers are often kept on their toes by exchange rate management because of its volatility and significance in attaining macroeconomic stability.

Comprehending the level of uncertainty surrounding economic policy of the leading oil producers in the globe and the fluctuations in their petroleum production in relation exchange rate earnings is crucial for executing exchange rate stabilization plans and evaluating regulatory measures to rectify macroeconomic disparities. Because globalization has created few-to-no barriers, unexpected conditions and events in developed countries can spread to developing and emerging nations. As a result, these nations experience macroeconomic instability for reasons unrelated to their own domestic policies (Jiang *et al*. 2019). However, the empirical investigation has mostly overlooked the impact of foreign exchange rate perturbations on the exchange rate. According to Jiang *et al*. (2019), even while domestic levels of uncertainty stay consistent, the domestic economy may be vulnerable to shocks from outside uncertainty. In a different study, Krol (2014) demonstrates that both foreign and local EPU can be responsible for exchange rate volatility. Since external shocks are frequently held accountable, either directly or indirectly, for unstable performance and/or macroeconomic instability, we investigate, in contrast to other research, the combined effect of domestic and international EPU on exchange rates across the ECOWAS member states.

Furthermore, a recent IMF research notes that external shocks are mostly to blame for the macroeconomic volatility observed in developing nations (IMF, 2024). By examining the impact of uncertainty around both local and international economic policies on the currency rate in 12 ECOWAS nations, studies have added to the expanding body of empirical research on uncertainty.

Our study's primary emphasis is Africa. First, we address the lack of comprehensive research on the relationship between EPU and the exchange rate in Africa by concentrating on the continent. African policymakers are uncertain about the appropriate measures to implement, as research appears to have concentrated on developed and rising nations. Furthermore, according to a report by the IMF, uncertainty plays a major role in the poorer economic performance of many nations, particularly developing economies in Africa, which experience severe shocks because there are no available policy measures to help lessen these shocks (see Ahir *et al*. 2018). Second, according to Kassouri and Altýnta (2020), 50% of Africa's export earnings come from a single commodity, and the majority of these nations strongly rely on a small number of main commodities, which causes volatile currency swings. Similar to emerging/developing nations, Africa has a less established foreign exchange market; as a result, these nations respond to shocks in various ways.

One of the economic explanations for why many well-endowed countries tend to expand at slower rates than their less endowed counterparts is the exchange rate's role as a conduit via which changes in the price of oil are transferred into the real sector. This is due to the co-movement that occurs between the exchange rate and the prices of the endowed resources, with oil being the key resource that moves the most and perhaps the most significant one given its non-renewable nature and economic impact to the global economy (Yu *et al*., 2023). The ongoing volatility in oil prices has severely impacted the value of the currencies of oil exporting nations, particularly emerging nations whose economies heavily rely on oil exports (Aleksandrova, 2016). This has sparked a good deal of empirical study on the correlation between exchange rate factors and oil prices, with conflicting results for oil-exporting nations. The majority of previous research has been on the linear link between oil prices and the calculation of exchange rates (Castro & Jiménez-Rodríguez, 2020). Particularly in emerging nations that export oil, the non-linear or asymmetric impacts of oil price on exchange rates have not yet received empirical attention. The research is devoted at investigating the dynamics between the uncertainty of news, oil price shocks, and exchange rate returns in developed nations.

We are motivated to investigate the impact of petroleum production output, uncertainty and exchange rate returns in the 3 largest oil producing nations in the world because of these nations' distinct features and their greatest percentage of the world's net worth. The following factors have led to the developed world's selection as the research location. First, with 58% of the global net worth, the developed nations comprise the most industrialized sample (WDI, 2022). Second, depending on nominal price and purchasing power parity, respectively, these countries represent more than 46% of the world's gross domestic products (OECD, 2023). Furthermore, these nations' economic performance has been considerably better over time. Additionally, they invest billions of dollars, which has improved these nations (Yuan *et al*., 2021). The research adds to the body of knowledge in a number of ways. First, this study investigates the impact of the oil price shock and news-based uncertainty on the exchange rate returns in rich and emerging nations using Markov Switching and DCC-GARCG modeling technique. Second, this study examines the impact of global uncertainty on the exchange rate as international shocks have an equal bearing on the local currency rate. Lastly, we distinguish between the effects on exchange rates in rich and developing nations of minor to big positive shocks to the price of oil and uncertainty, as well as the effects of minor to major negative shocks to the same. This study investigates how the price of oil and news base uncertainty affects the profits on exchange rates in industrialized and emerging nations. The following part offers the literature review; part 3 describes the methodology; Section 4 presents the data and analyzes the findings; and Section 5 concluded with some recommendations for further research and policy.

## 2. Literature Review

Regarding the literature on news-based uncertainty and exchange rate returns; Chen *et al*., (2019; Chen *et al*., 2020) found that there is a heterogeneous influence of economic policy uncertainty (EPU) on the exchange rate in China after using quantile regression to study the effect of EPU on the exchange rate in China. A few additional recent studies have also been done to look at the connection between exchange rate and economic policy uncertainty, or EPU. Bartsch (2019), for instance, employed GARCH models based on daily frequency data and came to the conclusion that using daily data increased the impact of EPU on the exchange rate. The nonlinear link between exchange rate and EPU has been extensively studied in recent research. For instance, Yin *et al*. (2017) used the quantile regression test to investigate the causal association between EPU and exchange rate. Their results showed that using quantile regression results in a more meaningful link. Moreover, Kido (2016) found a negative and statistically significant correlation between US-EPU and high-yield currencies in various nations, with the exception of the Japanese Yen, after using the DCC-GARCH model on monthly data to examine the spillover effect of US economic policy uncertainty on exchange rates. Kido (2018) examined the influence of US-EPU on Asian and international financial markets by factor-augmented vector auto-regression and discovered that rising US-EPU has a knock-on effect on commodity, exchange, and equities prices. Additionally, he came to the conclusion that although most other currencies depreciate, the Japanese yen appreciates in response to a rise in the US-EPU. His research also indicated that US-EPU had no impact on the Chinese equities market. It is also mentioned in the literature that macroeconomic variables are nonlinear over time. Numerous investigations have been carried out to emphasize the significance of nonlinear modeling. Numerous macroeconomic indicators, according to Lee and Lin (2012), exhibit structural fractures across time and represent nonlinear patterns in data sets. The nonlinearity in the data series is not captured by the linear models that are currently in use, according to Naifar and Al Dohaiman (2013).

Bildirici and Turkmen (2015) came to the conclusion that nonlinear models have a greater explanatory capacity than linear models. In ten developed and emerging nations, Krol (2014) investigated the impact of uncertainty in economic policy and general economic conditions on exchange rate volatility. The author discovered that the ambiguity surrounding economic policy has a greater influence on exchange rate volatility than does overall economic uncertainty. The author went on to say that both local EPU shocks and US-EPU shocks have an impact on the exchange rate in developed nations that are more linked with the US economy. Only local EPU influences the currency rate in emerging economies, which are less linked with the US.

Regarding previous researches done on the effect of oil price and exchange rate returns; Vochozka *et al.* (2020) using neural networks examined the influence of global crude oil prices on the EUR/USD exchange rate and discovered that the price of Brent crude oil has a considerable influence on the Euro-USD exchange rate, making it predictable. Chen *et al.* (2022) investigated the dynamic relationships and asymmetric spillover between the WTI crude oil prices and the exchange rates of six different currencies: the Canadian dollar, the Australian dollar, the Swiss franc, the Japanese yen, and the euro. The authors discovered that big economies and resource-based economies are the ones that transmit instability. Furthermore, this phenomenon varies over time, particularly in the wake of major world economic shocks like COVID-19. Jiang *et al.* (2022) discovered that COVID-19 caused a breach in the correlation between oil prices and currency rates. The bi-directional risk spillover between the currency rate and crude oil in emerging market countries was examined by Zhang and Qin (2022). The asymmetric bi-directional spillover between oil prices and currency rates was discovered by the study using copulas.

Mensi *et al.* (2022) used the Markov-Regime switching model to investigate the non-linear relationship between the price of gold, the RMB, and the price of oil. The investigation revealed that there were non-linear interactions among the factors. Furthermore, the Chinese currency rate (RMB) and gold prices are impacted by oil prices, although the influence of exchange rates on gold is minimal. The effect of oil prices on the currency rates of nations along the "Belt and Road Initiative" was examined by Sun *et al.* (2022). The authors checked the influence over a range of time periods using the empirical mode decomposition. The unequal influence on the exchange rates of nations that buy and export oil was discovered by the results.

Using data from 2004 to 2017, Ehikioya *et al.* (2020) investigated the relationship between changes in oil prices and real exchange rates in sub-Saharan African countries using the Johnson co-integration and vector error correction model. The research conducted by the authors indicates that there are dynamic linkages between the currency rates and oil prices of the sub-Saharan countries of Nigeria, Angola, Equatorial Guinea, Gabon, and the Republic of Congo. Finally, using vector error correction and co-integration techniques, Alam *et al.* (2020) investigated the link between oil prices and the Indian rupee in regard to the US dollar. The authors discovered both short- and long-term causal relationships between exchange rates and oil prices.'

Many studies that take into account the price of oil and exchange rates in 2021 have been carried out. In oil-exporting nations, Jin and Xiong (2021) discovered a strong negative correlation between exchange rates and oil prices during the oil price fall and a smaller correlation at other times. Razek & McQuinn, (2021) examines the connection between Saudi Arabia's international competitiveness and its behavioral exchange rate using the vector error correction model. The author comes to the conclusion that external factors most notably, the demand for oil determine Saudi Arabia's competitiveness. Cakan (2021) examined the influence of oil prices on the enterprises and investigated the link between the Turkish stock market and oil prices by manipulating several factors, including interest-rate nominal exchange rate. The results show that whereas large organizations are positively impacted by oil prices, small and mid-sized businesses are severely impacted. Liu *et al.* (2021) used time-varying copulas to examine the dependency between the variables as they investigated the link between oil prices and exchange rates in seven oil-importing nations. Bedin *et al.* (2021) used the Markov switching vector error correction model to investigate how Russia's GDP and exchange rate rely on oil prices. The data used by the author spans many distinct and well-defined regimes from 1999 to 2008. Findings show that in reaction to the shock of rising oil prices, the GDP adjusted more slowly whereas the actual exchange rate adjusted more quickly. The influence of oil and gas discoveries on the actual exchange rate was studied by Harding *et al.* in 2020. The discovery of oil and gas deposits has a 1.5% influence on the real exchange rate for every 10% of the nation's GDP, according to the author's research.

There are further comparable studies from the same year. Mukhtarov *et al.* (2021) use the structural vector autoregressive approach to analyze data from 1992 to 2019 in order to investigate the effects of oil price shocks on the exchange rate, total debt turnover, and GDP per capita in Azerbaijan. The authors discovered that while the exchange rate is negatively impacted, the oil price shock of oil-exporting nations has a beneficial impact on GDP per capita and overall trade turnover. Olstad (2021) looked at the correlation between the exchange rates of six net oil importing and exporting nations and the volatility of WTI and Brent crude oil prices. Dig-BEKK was used in the study to analyze data from February 1999 to May 2016. The findings show a correlation between the volatility of oil prices and the examined currencies' exchange rates throughout the global financial crisis and the European Union debt crisis. The link between the fluctuations in oil prices and the currency rates of five major oil exporting and importing nations was investigated by Hameed *et al.* (2021). The findings show that oil-exporting nations have more volatility spillover than oil-importing nations. Sohag *et al.* (2021) use the quintile-on-quintile method to investigate the correlation between oil prices and the Russian currency rate. Results show that the Russian ruble appreciates in relation to oil prices.

The impact of the COVID-19 pandemic and oil prices on the exchange rates of two oil-importing and three oil-exporting countries was investigated by Villarreal-Samaniego (2021) using the autoregressive distributed lag (ARDL). The exchange rates of the three nations and their mortality rates showed a positive association, but the five countries' exchange rates and oil prices showed a negative correlation, according to the author's findings. Chowdhary and Garg (2022) investigated the altered dynamics of crude oil prices and exchange rates during the Covid-19 pandemic and discovered a stronger relationship between crude oil and exchange rates. Subsequent findings suggest a more robust correlation between oil prices and currency rates subsequent to the global financial crisis. Akram (2020) looked on the connection between oil prices and exchange rates with regard to Canada and Norway. The study confirmed the existence of oil currencies by finding that fluctuations in the currency were caused by changes in oil prices that were driven by supply and demand.

## 3. Econometric Methodology

The study estimates the DCC-GARCH model due to Engle and Sheppard (2001) and the Markov switching variation vector autoregressive model (MS-VAR). The DCC technique models the data in a dynamic such that the constant correlation matrix denoted as $R_t$ depends on the time. Thus, we have:

$$S_t = C_t R_t C_t \tag{1}$$

Where $S_t$ is the conditional covariance matrix, the elements that are off the diagonals of $S_t$ becomes:

$$(S_t)_{ij} = s_{it}^{0.5} s_{jt}^{0.5} \rho_{ij,t}, i \geq 1, j \geq 1 \tag{2}$$

$C_t$ is the diagonal matrix containing conditional variances of the estimated univariate GARCH-models. Accordingly, the ARMA-DCC-GARCH model is given by equation (3):

$$C_t = \begin{pmatrix} s_{i,t}^{0.5} & 0 \ldots & 0 \\ 0 & s_{2,t}^{0.5} & . \\ 0 & 0 & s_{n,t}^{0.5} \end{pmatrix} \tag{3}$$

Such that,

$$s_{it} = \varpi_{it} + \sum_{j=1}^{q_i} \beta_{ij} r_{it-j}^2 + \sum_{j=1}^{p_i} \delta_{ij} s_{i,t-j} \tag{4}$$

The dynamic conditional correlation of the DCC-model has the following specification as found in the works of Engle and Sheppard (2001):

$$R_t = [\mathrm{I} \odot Q_t^{0.5}] Q_t [\mathrm{I} \odot Q_t^{0.5}] \tag{5}$$

Where $Q_t = [1 - \beta - \delta] D + \beta \upsilon_{t-1} \upsilon_{t-1}^{'} + \delta Q_{t-1}$; Qt is the covariance matrix, $D_t$ is the unrestricted correlation matrix for which we have:

$$\overline{Q} = Cov(\upsilon_t \upsilon_t^{'}) = E(\upsilon_t \upsilon_t^{!}) \tag{6}$$

The DCC-garch parameters are subject to the restrictions: $\beta, \delta \;\; \beta > 0, \delta > 0, \beta + \delta < 1$. The rescaling of equation (5) yields the correlation matrix such that the estimated matrix becomes:

$$[\mathrm{I} \odot Q_t^{0.5}] = \begin{pmatrix} \sqrt{q_{1,t}} & 0 \ldots & 0 \\ 0 & \sqrt{q_{2,t}} & . \\ 0 & 0 & \sqrt{q_{n,t}} \end{pmatrix} \tag{7}$$

The rescaling of $Q_t$ is guided by the fact that: $\rho_{i,j,t} \leq 1$ and the estimated correlations are given by:

$$r_t \left| \Phi_{t-1} \sim N[0, C_t R_t C_t] = N[0, S_t] \right. \tag{8}$$

The estimation was done based on the maximum likelihood function of the student's t distribution errors. The study estimated the MS-VAR model developed by Hamilton (1989, 1990) to ascertain the robustness of the DCC-GARCH model estimates. The MS-VAR model's empirical merit stems from its ability to instinctively detect structural changes, or apparent shifts in trending data to a new regime, and apply VAR estimation to each regime. For simplicity's sake, classify the economy into two states: low fluctuations and large fluctuations. Hence, the model's strength is based on a Markov process of switching between the two states. For parameter estimations that show persistent historical linear trends, the MS-VAR model estimation consistently produces smaller confidence ranges.

The MS-VAR as a univariate Markov variation model was developed by Hamilton (1989, 1990, and 2016) while it improved upon as a multivariable model by Krolzig (1997). Following the works of Krolzig (2013, 2006), we adopt the MS-VAR and the model is specified as follows:

$$EXR_r = b_1(s_t) + A_1(s_t)EXR_{r(t-1)} + A_1(s_t)EXR_{r(t-p)} + \upsilon,\ \ \upsilon_t \mid s_t \sim NID(0, \Omega_{st}) \tag{9}$$

The parameter change functions and the realized regime are given as equations (10) and (11):

$$b_1 A_1, ..., + A_p \Omega \tag{11}$$

$$s_t \in [1, 2, ..., N] \tag{12}$$

The rationale for adopting the Krolzig (2013, 2006)'s model is that it is dependable in modeling dynamic interactions amongst multivariate systems. Accordingly, the function defining dependence on parameters is given by:

$$s_t = \begin{cases} b_1 & if \quad s_t = 1 \\ b_N & if \quad s_t = M \end{cases} \tag{13}$$

The dynamic impact reaction function in MS VAR models is given as:

$$E_{\forall \eta}(g) = k[\sum_{l=0}^{d} A^l G F^{g-l}]\ \ \forall \eta, k = (I_l \quad 0 = k = 1_1^{'} \otimes I_l) \tag{14}$$

The simplified version of the MS-VAR model becomes as specified in equation (15):

$$EXR_r = A(\eta_t)_{EXRrt-1} + \upsilon_t, \eta_t = F\eta_{t-1} + e_t \tag{15}$$

Where $\upsilon_t$ *and* $e_t$ are the martingale differences such that the conditional expectation equation is specified as in equation (9).

$$E[EXR_{rt+g} \mid EXR_r, \eta_t] = \sum_{i=1}^{M} E[\upsilon_{it+g}\, EXR_{rt+g} \mid EXR_{rt}, \eta_t]$$
$$= (1_N^{'} \otimes I_l)E[EXR_{rt+g} \mid EXR_t = (1_N^{'} \otimes I_l)\pi^g(\eta_t \otimes EXR_{rt}) \tag{16}$$

$$\Rightarrow EXR_r = \sum_{i=1}^{M} \upsilon_{it} EXR_r$$

The corresponding impacts and reactions are as follows:

$$E_{\forall b_1}(g) = (1_N^{'} \otimes I_l)\pi^g(\eta_t \otimes \forall_\upsilon) \tag{17}$$

$$E_{\forall \eta}(g) = (1_N^{'} \otimes I_l)\pi^g(\forall \eta_t \otimes EXR_{rt}) \tag{18}$$

where: *EXRr (USD), EXRr(RUB) and EXRr(SAR)* are the exchange rate returns on the United States dollar, Russian Rubles and the Saudi riyal respectively, *OLPRO* is crude oil production proxied for petroleum output, *UNCERT* is measure of policy uncertainty, $\Sigma AR_1$, and $\Sigma AR_2$ are sum of non-switching regressors in regimes 1, and 2, $b_1$, $b_2$, $b_3$, $b_4$, $b_5$, $b_6$, $b_7$ are the coefficients of the constant, $ln_1$ (Sigma), and $ln_2$(Sigma) are the volatility coefficients of regime 1, and 2, $v_{it}$ is the representation of the residual series. The data were sourced from the database of World Bank. Petroleum output was measured as crude oil production, exchange returns were calculated as the logarithmic return for US dollar, Saudi Arabia riyal and Russia rubble as 100[ln(EXR)- ln(EXR(-1)]. There is no consensus yet in the literature as to the best method for deriving economic policy uncertainty. Lensink *et al* (1999) constructed uncertainty measure based on the GARCH modeling that allows the time dependence of the second moment of random variables. According to Feng (2001), inflation is caused mostly by political uncertainty and is thus a good proxy for policy uncertainty. Following the works of Korley and Giouvris (2022), Grier and Tullock (1989), De Gregorio (1993), and Feng (2001); we used the square root of the variance of inflation as a measure of macro-economic policy uncertainty. By this method, we constructed policy uncertainty as the standard deviation of the unpredictable component of a stochastic process. The unanticipated component of the policy is the standard deviation of the stochastic disturbances. The standard deviation of the residuals is taken as the variable for policy uncertainty. Thus, the calculation process entails fitting a first-order autoregressive process specified as follows: $\pi_t = \zeta_0 + \zeta_1 \pi_{t-1} + e_t$ ; where $\pi_t$ is inflation, $\zeta_1$ is the coefficient of the autoregressive inflation component, and $e_t$ is the stochastic disturbance term. The policy in question is monetary and fiscal policies in relation to the workings of the macro economy of each of the United States, Saudi Arabia and Russia. Thus, inflation was measured by the consumer price index for each country. Weekly series were utilized from January 2000 to August 2024. In the estimation of parameters of DCC-GARCH model the maximum likelihood method with a student t-distribution was made functional.

## 4. Results and discussion

To prevent erroneous regression, we examine the variables' integration order and stationarity in Table 2. The research utilized two distinct tests to assess incidence or otherwise of unit root. These are the ADF and the PP tests. In the level series, the ADF and PP tests were unable to reject the null hypothesis of a unit root, except EXRr(SAR). However, ADF and PP both rejected the null hypothesis for the series' first difference, indicating that the first-order differences of the variables were stationary at the 5% level. As a result, the series were integrated at order I (1) with the exemption of the return on riyal.

**Table 2: Unit Root Results**

| *Variables* | *ADF* | | *PP* | | *Remarks* |
|---|---|---|---|---|---|
| | *Level* | *First Diff.* | *Level* | *First Diff.* | |
| EXRr(USD) | 1.6578 | 26.8513*** | -0.5421 | -7.4356*** | I(1) |
| | (0.3423) | (0.0000) | (0.2935) | (0.0000) | |
| EXRr(SAR) | 183.459*** | - | 1.6578 | 4.6578** | I(0) |
| | (0.0000) | | (0.0173) | (0.0013) | |
| EXRr(RUB) | 7.38287 | 9.3674*** | 1.2389 | 29.1523*** | I(1) |
| | (0.7809) | (0.0000) | (0.9783) | (0.0000) | |
| $OLPRO_{USD}$ | 1.2165 | 13.263** | -0.13650 | -10.0456*** | I(1) |
| | (0.7275) | (0.0000) | (0.4457) | (0.0000) | |
| $OLPRO_{SAR}$ | 1.3793 | 9.2673*** | 0.3692 | 11.3675*** | I(1) |
| | (0.2387) | (0.0000) | (0.1225) | (0.0000) | |
| $OLPRO_{RUB}$ | 1.5894 | 6.8492 | 1.2345 | 16.4352*** | I(1) |
| | (0.3692) | (0.000) | (0.1325) | (0.0000) | |
| UNCERT | 1.6573 | 15.095*** | 1.06741 | -8.59579*** | I(1) |
| | (0.1293) | (0.0000) | (0.2554) | (0.0000) | |

**Sources**: Authors' own estimation with E-views 13 program

In conducting the co-integration test, the existence of a possible co-integration relationship amongst the variables was tested based on the Maximum Eigenvalue and Trace statistics. The results of Table 3 show that the tests have a critical value reported in bracket below each statistics that is lesser than the test statistics and indeed permits us to reject the null hypothesis that co-integration is non-existent.

**Table 3: Co-integration Test Results**

| $H_0$ | $H_1$ | *Eigenvalue* | *Max-eigen statistic* | *Trace statistic* |
|---|---|---|---|---|
| | | | | |
| $r = 0$ | $r \geq 1$ | 0.0045 | 39.46791<br>(27.48094) | 57.43921<br>(46.4879) |
| $r \leq 1$ | $r \geq 2$ | 0.0691 | 27.3629<br>(18.9403) | 40.95231<br>(35.5876) |
| $r \leq 2$ | $r \geq 3$ | 0.0523 | 19.8792<br>(15.9816) | 37.62892<br>(20.4899) |
| $r \leq 3$ | $r \geq 4$ | 0.0163 | 14.86397<br>(11.09450) | 26.13542<br>(18.4094) |
| $r \leq 4$ | $r \geq 5$ | 0.0074 | 12.58279<br>(10.0797) | 13.2563<br>(10.9872) |
| | | | | |
| $H_0$ | $H_1$ | Eigenvalue | Max-eigen statistic | Trace statistic |
| $r = 0$ | $r \geq 1$ | 0.01556 | 21.58760<br>(24.8092) | 45.09852<br>(50.21789) |
| $r \leq 1$ | $r \geq 2$ | 0.00982 | 16.25678<br>(17.9875) | 34.08751<br>(36.92132) |
| $r \leq 2$ | $r \geq 3$ | 0.07691 | 14.13679<br>(18.0566) | 29.82546<br>(30.17679) |
| $r \leq 3$ | $r \geq 4$ | 0.00531 | 13.08976<br>(13.12654) | 25.06249<br>(26.95321) |
| $r \leq 4$ | $r \geq 5$ | 0.00963 | 11.02675<br>(12.63092) | 20.98754<br>(22.96523) |
| | | | | |
| $H_0$ | $H_1$ | Eigenvalue | Max-eigen statistic | Trace statistic |
| $r = 0$ | $r \geq 1$ | 0.09876 | 25.4872<br>(27.1189) | 59.3673<br>(62.4894) |
| $r \leq 1$ | $r \geq 2$ | 0.01346 | 16.6357<br>(19.5621) | 55.9789<br>(60.6187) |
| $r \leq 2$ | $r \geq 3$ | 0.02546 | 19.2483<br>(22.3879) | 43.0975<br>(44.9810) |
| $r \leq 3$ | $r \geq 4$ | 0.07658 | 20.0165<br>(21.2893) | 37.0986<br>(39.0198) |
| $r \leq 4$ | $r \geq 5$ | 0.01379 | 14.8759<br>(16.1095) | 30.9885<br>(35.6799) |

*Sources:* Authors' own estimation with E-views 13 program

There are 3 different Markov regime switching regression estimations, MS-VAR results for United States, MS-VAR results for Saudi Arabia, and MS-VAR results for Russia. The best MS-VAR model was chosen on the basis of the smallest value of the AIC criterion and the largest log-likelihood value while the appropriate lag length was selected on the basis of the votes donated by AIC, SIC, HQ, and BIC respectively. Accordingly, the MS (2)-VAR(2) model was chosen for each country. There are 3 vectors in the MS(2)-VAR(2) model (crude oil production, economic policy uncertainty and exchange rate returns for the US dollar, Saudi Arabia riyal and Russia rubble) with two regimens and 2 lags. There are two regimes, Regime 1 and Regime 2 respectively. Regime 1 is the period of low turbulence while Regime 2 is the period of high turbulence in the world economy. The period in which the dynamic effect of uncertainty on petroleum production is significant in the model is the high turbulence period (Regime 2). When the coefficients of the variables are checked, it is seen that uncertainty had a negative coefficients of -0.1245*** and -0.1492***on crude oil production of the United States; had negative coefficients of -0.0421*** and -0.1206***on crude oil production of the Saudi Arabia, and had negative coefficients -0.0138** and -0.0945***on crude oil production of the Russia respectively. The negative returns effects of policy uncertainty in the 3 countries during the highly turbulent era are measured by the coefficients; -0.0157*** and -0.1220***;-0.1206*** and -0.1673***; and -0.1738*** and -0.0645 respectively.

Crude oil production variable is positive on returns of US dollar on the third vector in both periods of low and high turbulence, the coefficients are 0.1896** and 0.0346***in regime 1 while in regime 2, the coefficients are 0.1900 and 0.1203. Only the effects of the first regime are significant. Comparably, in Saudi Arabia, petroleum production is positive on returns of Saudi Arabia riyal on the third vector in both periods of low and high turbulence, the coefficients are 0.0129*** and 0.0341******in regime 1 while in regime 2, the coefficients are 0.1263*** and 0.0341*** respectively. The positive effects are significant for both regimes of analysis. For the Russian economy, crude oil production variable is positive on returns of Russia rubble on the third vector in only in the low turbulence era (Regime 1) with the coefficients given as 1.0123*** and 0.1206*** while in regime 2, the crude oil production variable is negative significant on returns of Russia rubble with effects measured by the coefficients, -0.2309** and 0.8405**. In sum, only in the case of Russia, we had negative nexus between petroleum output growth and returns on the rubble for both Regime 1 and Regime 2 respectively. This could be as a result of the instability, unpredictability and unrest associated with the Russia takeover of Ukraine.

According to the diagnostics tests, each of the MS(2)-VAR(2) model in Tables 4, 5 and 6 are statistically robust. This is made evident by the transition matrices, filtered probability curves and the regime probabilities. The transition probability matrices for the United States, Saudi Arabia and Russia are displayed consecutively below the regime probability. For the United States of America; in the low turbulent period, the US economy stayed for 6.5142 weeks and thereafter trailed by an extremely turbulent history of 19.3862 weeks with a 26.849% probability and adversely influenced returns and petroleum production of the US during the period. Similarly, in Saudi Arabia, the nation's economy stayed in the low turbulent era for 18.3809 weeks and subsequently trailed by an extremely turbulent history of 13.2561weeks with an 11.32% probability. In this period, return on the riyal and petroleum production was precariously affected. The Russian economy remained in the low turbulent era for 14.1467 weeks and afterwards trailed by an extremely turbulent history of 48.0358 weeks with a 29.736% probability. In this period, return on the rubble and petroleum production was harmfully affected.

Specifically, the transition probabilities of the United States demonstrates that the probability of staying in the same regime in the next period while Regime 1 is in the low volatile or turbulent period is 83.729%, while the probability of staying in the same regime in regime 2 characterized by extremely unrest and uncontrolled period is 69.852%. In Regime 1, the probability of switching to Regime 2 in the next period is 26.849%, and the probability of switching back to Regime 1 is 39.453%. According to the Saudi Arabia transition matrix, the likelihood of remaining in the same regime during Regime 1's low volatile or turbulent period is 96.53%, whereas the likelihood of doing so during Regime 2's extremely unrest and turbulent period is 84.518%. In the following period, there is an 11.32% chance of moving from Regime 1 to Regime 2, and a 16.148% chance of going back to Regime 1. In Russia, transition matrix shows that the probability of waiting in the same regime in the succeeding period while Regime 1 is in the low volatile period is 79.256%, while the probability of staying in the same regime in the regime 2 extremely unrest and turbulent period is 82.992%. The probability of switching from Regime 1 to Regime 2 in the next period is 29.734%, and the probability of switching back to Regime 1 is 10.387%.

**Table 4: Markov Regime Switching VAR Results for United States**

| Variable | $\Delta \ln OLPRO_{US}$ | $\Delta \ln UNCERT$ | $\Delta \ln EXRr(USD)$ |
|---|---|---|---|
| Regime 1 | | | |
| constant | 1.1943 | 1.0250 | 0.2901 |
| $\Delta \ln OLPRO_{US}(-1)$ | 1.0016*** | 0.1042 | 0.1896** |
| $\Delta \ln OLPRO_{US}(-2)$ | 0.1372*** | 0.1684 | 0.0346*** |
| $\Delta \ln UNCERT(-1)$ | -0.1605 | 0.1904*** | -0.0233 |
| $\Delta \ln UNCERT(-2)$ | -1.0241 | 0.0151*** | -0.0149 |
| $\Delta \ln EXRr(USD)(-1)$ | 0.1092 | 0.0381 | 0.1279*** |
| $\Delta \ln EXRr(USD)(-2)$ | 0.0131 | 0.1394 | 0.0564*** |
| Regime 2 | | | |
| Constant | 0.6023*** | 1.0186 | 0.5214*** |
| $\Delta \ln OLPRO_{US}(-1)$ | 0.1045 | 0.0271 | 0.1900 |
| $\Delta \ln OLPRO_{US}(-2)$ | 0.0934 | 0.0145 | 0.1203 |
| $\Delta \ln UNCERT(-1)$ | -0.1245*** | 0.0123*** | -0.0157*** |
| $\Delta \ln UNCERT(-2)$ | -0.1492*** | 0.2719*** | -0.1220*** |
| $\Delta \ln EXRr(USD)(-1)$ | 0.0751 | 0.0316 | 0.2516*** |
| $\Delta \ln EXRr(USD)(-2)$ | 0.0226 | 1.1408 | 0.0379*** |
| **Diagnostics** | | | |
| DW statistic | 2.03874 | Normality | 109.387*** |
| Portmanteau(30) | 678.920 | Linearity LR Test | 4289.56*** |
| **Regime Probabilities** | | | |
| Regime(s) | Probability | Duration (Weeks) | Observations |
| Regime 1 | 0.9240 | 6.5142 | |
| Regime 2 | 0.9516 | 19.3862 | |
| **Transition probability matrix** | | | |
| $P_{r(United\ States)} = \begin{bmatrix} Regime1 & 0.83729 & 0.26849 \\ Regime2 & 0.19453 & 0.69852 \end{bmatrix}$ | | | |

*Note:* *** Significant at 1%, ** Significant at 5%, *Significant at 10%
*Sources:* Authors' own estimation with E-views 13 program

**Table 5: Markov Regime Switching VAR Results for Saudi Arabia**

| Variable | $\Delta \ln OLPRO_{SA}$ | $\Delta \ln UNCERT$ | $\Delta \ln EXRr(SAR)$ |
|---|---|---|---|
| Regime 1 | | | |
| constant | 1.3866** | 1.0657 | 0.1054 |
| $\Delta \ln OLPRO_{SA}(-1)$ | 0.0129*** | -0.0162 | 1.0123*** |
| $\Delta \ln OLPRO_{SA}(-2)$ | 0.0341*** | -0.0154 | 0.1206*** |
| $\Delta \ln UNCERT(-1)$ | -0.5206 | 0.2384*** | -0.1473 |
| $\Delta \ln UNCERT(-2)$ | -0.6173 | 0.1657*** | -0.1276 |
| $\Delta \ln EXRr(SAR)(-1)$ | 0.0276*** | 0.0179 | 0.1806*** |
| $\Delta \ln EXRr(SAR)(-2)$ | 0.0513*** | 0.0138 | 0.1294*** |
| Regime 2 | | | |
| constant | 0.2045 | 0.5728 | 0.1728 |
| $\Delta \ln OLPRO_{SA}(-1)$ | 0.1728** | -0.0126 | 0.1263*** |
| $\Delta \ln OLPRO_{SA}(-2)$ | 0.0196*** | -0.0341 | 0.0341*** |
| $\Delta \ln UNCERT(-1)$ | -0.0421*** | 0.5206*** | -0.1206*** |
| $\Delta \ln UNCERT(-2)$ | -0.1206*** | 0.1673*** | -0.1673*** |
| $\Delta \ln EXRr(SAR)(-1)$ | 0.0615 | -0.1276 | 0.1472*** |
| $\Delta \ln EXRr(SAR)(-2)$ | 0.0196 | -0.3506 | 0.1500*** |
| **Diagnostics** | | | |
| DW statistic | 2.1679*** | Normality | 187.126*** |
| Portmanteau(30) | 570.146 | Linearity LR Test | 5791.03*** |
| **Regime Probability** | | | |
| Regime(s) | Probability | Duration (Weeks) | Observations |
| Regime 1 | 0.8279 | 18.3809 | |
| Regime 2 | 0.8065 | 13.2561 | |
| **Transition Probability Matrix** | | | |
| $P_{r(Saudi\ Arabia)} = \begin{bmatrix} Regime1 & 0.96530 & 0.11320 \\ Regime2 & 0.16148 & 0.84518 \end{bmatrix}$ | | | |

*Note:* *** Significant at 1%, ** Significant at 5%, *Significant at 10%
*Sources:* Authors' own estimation with E-views 13 program

**Table 6: Markov Regime Switching VAR Results for Russia**

| Variable | $\Delta \ln OLPRO_{RU}$ | $\Delta \ln UNCERT$ | $\Delta \ln EXRr(RUB)$ |
|---|---|---|---|
| Regime 1 | | | |
| constant | 0.0341** | 0.03421 | 0.0184*** |
| $\Delta \ln OLPRO_{RU}(-1)$ | 0.5206*** | 0. 5206 | 0.1038** |
| $\Delta \ln OLPRO_{RU}(-2)$ | 0.4673*** | 0.4673 | 0.2945*** |
| $\Delta \ln UNCERT(-1)$ | -0.1326 | 0.9326*** | -0.1728 |
| $\Delta \ln UNCERT(-2)$ | -0.8506 | 0.7506*** | -0.1296 |
| $\Delta \ln EXRr(RUB)(-1)$ | 0.5494 | 0.2494 | 0.0341** |
| $\Delta \ln EXRr(RUB)(-2)$ | 0.4622*** | 0.3624 | 0.1506*** |
| Regime 2 | | | |
| Constant | 0.0036*** | -0.0573 | -0.1052** |
| $\Delta \ln OLPRO_{RU}(-1)$ | 0.5309*** | -0.1421 | -0.2309** |
| $\Delta \ln OLPRO_{RU}(-2)$ | 0.0214*** | 0.5068 | 0.8405 |
| $\Delta \ln UNCERT(-1)$ | -0.0138** | 0.1546*** | -0.1738*** |
| $\Delta \ln UNCERT(-2)$ | -0.0945*** | 0.0276*** | -0.0645*** |
| $\Delta \ln EXRr(RUB)(-1)$ | 0.1268 | -0.1306 | 0.1628*** |
| $\Delta \ln EXRr(RUB)(-2)$ | 0.1096 | -0.1455 | 0.1293** |
| **Diagnostics** | | | |
| DW statistic | 2.0016 | Normality | 79.367*** |
| Portmanteau(30) | 792.387 | Linearity LR Test | 9263.27*** |
| **Regime Probability** | | | |
| Regime(s) | Probability | Duration (Weeks) | Observations |
| Regime 1 | 0.9367 | 14.1467 | |
| Regime 2 | 0.9725 | 48.0358 | |
| **Transition Probability Matrix** | | | |
| $P_{r(Russia)} = \begin{bmatrix} Regime1 & 0.79256 & 0.29734 \\ Regime2 & 0.10387 & 0.82992 \end{bmatrix}$ | | | |

*Note:* *** Significant at 1%, ** Significant at 5%, *Significant at 10%
*Sources:* Authors' own estimation with E-views 13 program

Figure 5 below is the plot of the smoothed probability

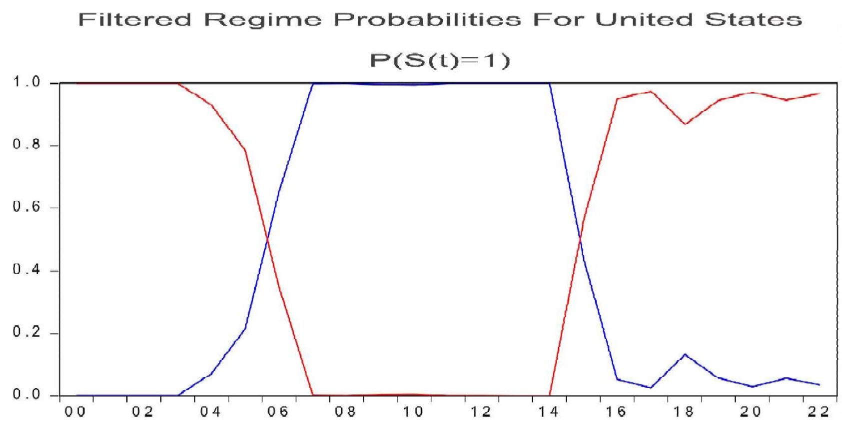


**Figure 5: Filtered Regime Probabilities plot for United States**

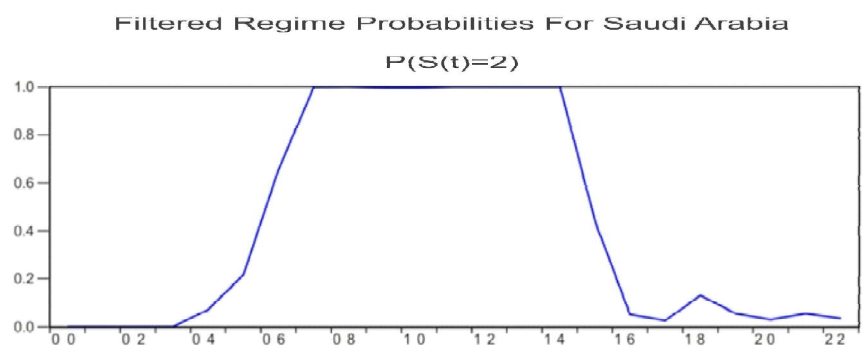


**Figure 6: Filtered Probabilities plot for Saudi Arabia**

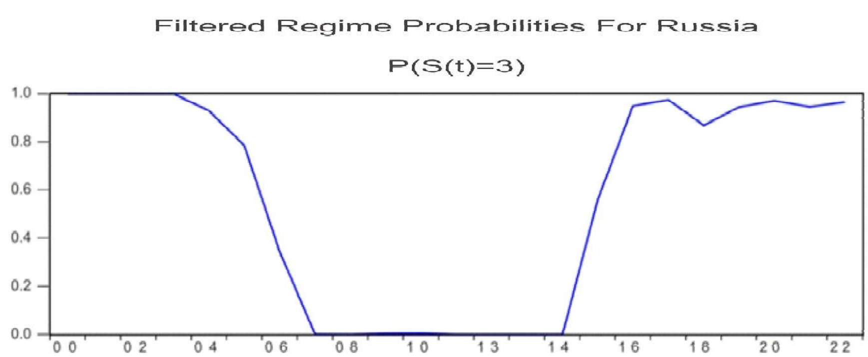


**Figure 6: Filtered Probabilities plot for Russia**

To investigate the ARCH effect on the variables, the study used the ARCH test. The heteroscedasticity test findings for the series are displayed in Table 7, and with an observed R-squared of 10.38261 and a p-value of 0.0004 for the US, it are statistically significant at a 5% level. Given that the p-value is below the necessary 5%, this suggests that the variables have an ARCH effect for the United States. This finding validates the suitability of a DCC-GARCH model by pointing to the impact of prior period exchange rate returns in relation to US dollars.

**Table 7: ARCH Effect (Heteroscedasticity) Test for Leading Oil Producers in the Globe**

| | |
|---|---|
| *United States* | |
| F-statistic | 17.87424 |
| Obs*R-squared | 10.38261 |
| Prob. F(1,20) | 0.0004 |
| Prob. Chi-Square(1) | 0.0013 |
| *Saudi Arabia* | |
| F-statistic | 10.3893 |
| Obs*R-squared | 7.38020 |
| Prob. F(1,20) | 0.0012 |
| Prob. Chi-Square(1) | 0.0015 |
| *Russia* | |
| F-statistic | 20.3487 |
| Obs*R-squared | 13.5487 |
| Prob. F(1,20) | 0.0022 |
| Prob. Chi-Square(1) | 0.0045 |

*Sources:* E-views output

Table 8 presents the bivariate DCC-GARCH (1, 1) results for US. Table 8's findings indicate a strong and positive dynamic link between exchange rate returns and NEWS. These currencies gain value relative to the US dollar when oil prices surprise upward. These are in line with our priors: rising oil prices move in tandem with higher, commodity-based local currencies. Local currency and news have a strong and positive dynamic relationship. The findings show that, for any currency based on commodities, the time-varying correlations between exchange rates and uncertainty, and production of petroleum products are statistically significant. For all countries; the conditional mean equations were passed test of significance at the 5% level. All the parameters for conditional variances and correlations were significant as reported by the zero probability value. The parameter estimate of 8.9275 is an indication that the distributional adjustment with the students't - distribution to the data was appropriate. The coefficient of past exchange rate return reported is 0.31247, and for the US dollar, 0.14263 for the Saudi Arabia riyal and 0.15962 for the Russia rubble respectively. This passed on positive dynamism in the relation between the previous and currency returns.

The variance estimates of the three countries significantly characterized volatility dynamics between the demand for crude oil output and exchange rate returns. The positive coefficients of 0.01653 and 1.37282; 0.12379 and 0.40728; and 0.61270 and 0.10942; alongside significant z-statistics and zero p-values for the first and second lags of petroleum output imply substantial correlation and mean reversion between exchange rate earnings and petroleum output for the three countries. The negative coefficients of -0.08315 and -0.09162; -0.01326 and -0.01579; and -0.05300 and -0.42831; for first and second lagged economic policy uncertainty all had significant z-statistics. This implies considerable unpredictability of economic policy on the return of each of the three currencies. Having depicted a significant negative dynamic adjustment between policy uncertainty and currency return, our results align with those of Abid (2020), and Zhou *et al.* (2020), Zachary (2019), Raza *et al.* (2018) and Christou *et al.* (2018). Abid (2020) established that currency exchange rate falls in response to higher EPU in emerging countries of Brazil, South Korea, Chile, India, and Mexico based on an ARDL model. Using GARCH_Midas, the empirical finding obtained by Zhou *et al.* (2020) upholds that foreign EPU significantly affected Chinese exchange rate volatility. Zachary (2019) employed GARCH models and provided evidence that EPU contributes to exchange rate volatility. According to Zachary (2019), EPU was the cause of exchange rate volatility in UK. Raza *et al.* (2018) reported that EPU transmits risk adversely affects the exchange rate returns. Christou *et al.* (2018) utilized the quantile regression to establish that EPU as a useful predictor of exchange returns and volatility. Our results differ from the prevailing findings of Korley and Evangelos (2023), and Chen *et al.* (2020). Korley and Evangelos (2023) found that domestic EPU has a positive effect on exchange rates in the long run for Non-CFA areas; and that foreign EPU leads to appreciation in the long run and depreciation in the short run. Their results further uphold that domestic EPU does not explain exchange rate fluctuations in the short run. Chen *et al.* (2020) reported that EPU for China has a positive and significant impact on China's exchange rate volatility, and the EPU of Japan and Europe display an inverted-U-shape correlation with exchange rate volatility in China.

**Table 8: Results of DCC-GARCH for EXRr(USD)**

| *Variables* | *Coefficient* | *Std. Error* | *z-Statistic* | *Prob.* |
|---|---|---|---|---|
| | Conditional means and variances equations | | | |
| $\alpha_{OLPROUS}^{(-1)}$ | 0.01653 | 0.00037 | 44.6757 | 0.0000 |
| $\gamma_{OLPROUS}^{(-2)}$ | 0.37282 | 0.01150 | 119.3757 | 0.0000 |
| $\tau_{UNCERT}^{(-1)}$ | -0.08315 | 0.00533 | -15.6004 | 0.0001 |
| $\beta_{UNCERT}^{(-2)}$ | -0.09162 | 0.01518 | -6.03560 | 0.0000 |
| $\phi EXR_r(USD)(-1)$ | 0.31247 | 0.01412 | 22.1296 | 0.0000 |

*Source:*

**Table 9: Results of DCC-GARCH for EXRr(SAR)**

| *Variables* | *Coefficient* | *Std. Error* | *z-Statistic* | *Prob.* |
|---|---|---|---|---|
| | Conditional means and variances equations | | | |
| $\alpha_{OLPROUS}^{(-1)}$ | 0.12379 | 0.00124 | 99.8306 | 0.0000 |
| $\gamma_{OLPROUS}^{(-2)}$ | 0.40728 | 0. 10033 | 4.0594 | 0.0012 |
| $\tau_{UNCERT}^{(-1)}$ | -0.01326 | 0.00128 | -10.3594 | 0.0027 |
| $\beta_{UNCERT}^{(-2)}$ | -0.01579 | 0.00174 | -9.0747 | 0.0000 |
| $\phi EXR_r(SAR)(-1)$ | 0.14263 | 0.00016 | 516.4375 | 0.0000 |

**Table 10: Results of DCC-GARCH for EXRr(RUB)**

| *Variables* | *Coefficient* | *Std. Error* | *z-Statistic* | *Prob.* |
|---|---|---|---|---|
| | Conditional means and variances equations | | | |
| $\alpha_{OLPROUS}^{(-1)}$ | 0.61270 | 0.03871 | 26.1612 | 0.0000 |
| $\gamma_{OLPROUS}^{(-2)}$ | 0.10942 | 0.01538 | 7.1144 | 0.0001 |
| $\tau_{UNCERT}^{(-1)}$ | -0.05300 | 0.01782 | -2.9742 | 0.0027 |
| $\beta_{UNCERT}^{(-2)}$ | -0.42831 | 0.00287 | -149.2369 | 0.0000 |
| $\phi EXR_r(RUB)(-1)$ | 0.15962 | 0.01823 | 8.7592 | 0.0000 |

**Table 11: Results* of DCC-GARCH**

| | | | | |
|---|---|---|---|---|
| | conditional correlation equation | | | |
| $\beta$ | 0.0586 | 0.0029 | 0.0000 | |
| $\phi$ | 0.7893 | 0.0056 | 0.0000 | |
| $\upsilon$ | 8.9275 | 0.2734 | 0.0000 | |

*Stability condition: $\beta + \phi < 1$ is fulfilled empirically

## 5. Conclusion

This study uses a quantitative methodology to examine the dynamics connectedness amongst policy uncertainty, petroleum output, and the exchange rate returns of the leading petroleum producing nations in the world. The DCC-GARCH model and the Markov-Switching VAR regression techniques were utilized assess the dynamism. The following is a summary of our primary findings: there is evidence of substantial correlation and mean reversion between exchange rate earnings and petroleum output for the three countries. The time-varying correlations between exchange rates and uncertainty, and production of petroleum products are statistically significant. The uncertainty index is proven to have adverse impact on returns. To be precise, we observed considerable adverse effect of the unpredictability associated with economic policy on return of each of the three currencies. There are times of high and low volatility for currency return, petroleum production and policy uncertainty. The estimation reveals that there is considerable evidence of correlation amongst the three variables across the petroleum market and currency market especially in the era of turbulence, with the conditional correlations between these series changing over time and displaying volatility for each country. Our findings have significant ramifications for investors since they show that when creating a more successful foreign currency market investment strategy, one must take the dynamics of oil price shocks into account. Furthermore, our findings can help monetary authorities and central banks stabilize exchange rates and put strong measures in place to support their currencies during times of extreme volatility.

Despite the fact that the economies researched in this study are not under pressure from concerns relating to the forex market; unpredictable policy events have happened in the exchange rate market. Hence, there is significant spillover turbulence effect from the petroleum market to the forex market especially in times of crisis. This research provides both market investors with a thorough grasp of how to formulate investment strategies for managing a portfolio. This study is useful to policymakers in developing monetary and fiscal policies, especially in economies that rely heavily on oil. Besides, the oil supply network has seen disruptions due to various geopolitical conflicts; examining the connection against the backdrop of these hitches may be an essential subject for further investigation.

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## *Appendix 1: Plots of returns*

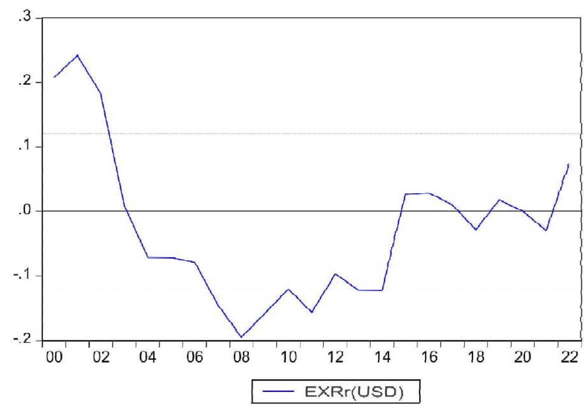


**Figure A1: Plot of Exchange rate return on US dollar**

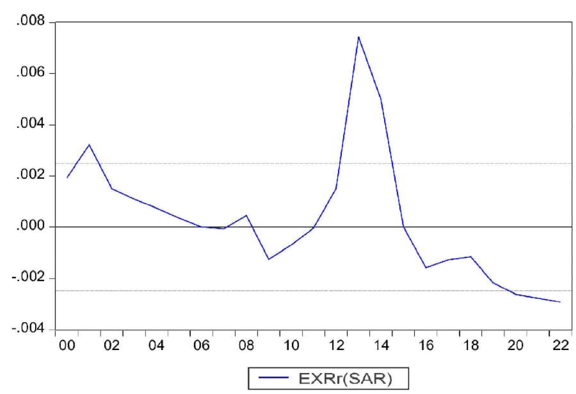


**Figure A2: Plot of Exchange rate return on Saudi Arabia riyal**

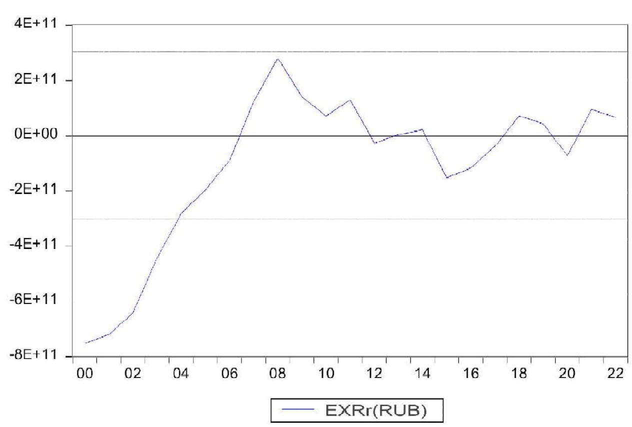


**Figure A3: Plot of Exchange rate return on Russia rubble**