EJEM
Econ.J.Emerg.Mark.

Economic Journal of Emerging Markets
Available at https://journal.uii.ac.id/jep

Exchange rates and oil price under uncertainty and regime switching: A Markov-switching VAR approach

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Article Info

Article history:
Received 23 June 2021
Accepted 23 September 2021
Published 1 October 2021

JEL Classification Code:
C32, C51, H12.

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DOI: 10.20885/ejem.vol13.iss2.art9

Abstract

Purpose — This paper analyses the effects of the US economic policy uncertainty index and oil price changes on the dollar exchange rate over a monthly period from January 2006 to August 2020.

Methods — This paper uses the Markov-switching Vector Auto-Regressive (VAR) model.

Findings — The results show that the sharp decline regime in the exchange rate is the most stable. In addition, the impact of the oil price on the exchange rate of the concerned currencies is stronger than the effect of EPU on the exchange rate of these currencies. We also find that most of the effects of oil prices were negative, while positive for the Canadian dollar and the Japanese yen exchange rate.

Implications — Addressing this investigation contributes to many of the areas covered in recent macroeconomic and finance research. Moreover, such research can help predict changes in currency and oil prices better and create profitable investment and hedging strategies for currencies and oil.

Originality — We consider the effect of economic policy uncertainty (EPU) and oil price changes on the relationships between those markets and study these relationships under different market conditions.

Keywords — oil price, exchange rate, Markov switching.

Introduction

The coronavirus (COVID-19) pandemic has created an unprecedented economic and financial crisis. In contrast, the measures necessary to contain the virus have led to an economic downturn and sharp fluctuations in oil prices; it has become a general economic crisis (Liu, Sun, & Zhang, 2020). Notably, the COVID-19 crisis has proven that global economies are fragile and can be affected by crises (Corbet, Larkin, & Lucey, 2020), similar to the 2008 global financial crisis that negatively affected financial markets. Some researchers, such as Baker et al. (2020), found that the current COVID-19 pandemic has a more significant impact on stock market performance than any previous health crisis. Furthermore, there is a great degree of uncertainty at present about how severe and long they are. The latest global financial stability report shows that the financial regime is already severely affected, and the intensification of the crisis could impact global financial stability (Padhan & Prabheesh, 2021). A recent study by Chkir, Guesmi, Brayek, and Naoui (2020) shows that the impact of oil price changes on the exchange rate markets varies in size, and its importance is based on the distribution of exchange rate returns. They also found that the response of currency

P ISSN 2086-3128 | E ISSN 2502-180X

markets to oil price movements changes between countries and oil price regimes and is more severe during highly volatile regimes.

The oil price shock is the main source of movement in the real exchange rate of the USD (Albulescu & Ajmi, 2021). When analyzing the relationship between oil prices and currency exchange rates, the problem is the possibility of two-way mutual causality of indicators. The first channel is based on trading conditions. For oil-importing countries, the latest price increase leads to a deterioration in the trade balance and subsequent depreciation of the national currency. The second channel finds its embodiment through the effect of wealth. An increase in oil prices leads to a shift in welfare from importers to exporters, which entails a change in the exchange rate of importing countries due to current account deficits and investment outflows (Walid, Chaker, Masood, & Fry, 2011).

The exchange rate is one of the key channels through which the oil price in dollars is transferred to the real economy (see Nouira, Amor, & Rault, 2019). Therefore, the US dollar movements are considered a predictive power in the international energy market. Zhang (2013) regimes that the dollar price of oil gives the impression of rising with the depreciation of the U.S. dollar. Some studies have found a relationship between the price of oil and the dollar's exchange rate (Turhan, Hacihasanoglu, & Soytas (2013); Aimer (2016, 2017, 2019a, 2019b)).

Since the US currency is the reference currency on the oil market, the question of possible links between oil prices and the dollar price seems particularly crucial. This question is particularly acute because of recent fluctuations in the oil price, especially since the early 2000s. Since 2002, and if we ignored the downward correction in July 2008, the oil price has been on an overall upward trend. At the same time, the dollar has depreciated (see Figure 1); it seems that crude prices and the dollar evolve in a similar way in relatively "calm" periods. When dollar movements are more pronounced, the direction of the relationship appears to be reversed. An inverse relationship is also observed over the period 2002-July 2008, the price of oil increases, while the dollar tends to depreciate. Therefore, it indicates that the relationship between the two variables is not unequivocal and depends on the period considered. On the other hand, visual observation suggests that the price of crude tends to be ahead of the dollar. In other words, if a causality between the two variables exists, it seems to operate from the price of oil towards the dollar.

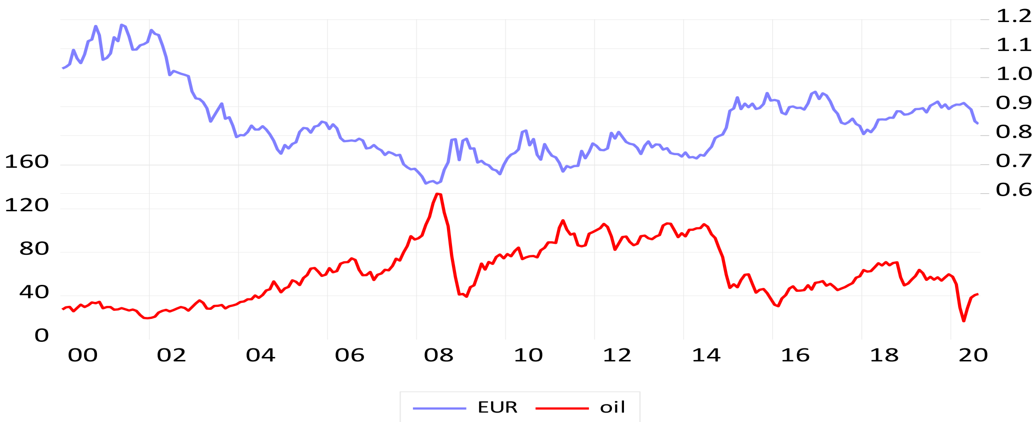

Figure 1. WIT crude oil prices and the exchange rate of the USD/EUR.

The purpose of this study is to analyze the effects of oil price movements and economic policy uncertainty on exchange rates using an MS-VAR model. Since the MS-VAR model includes information on the probability density function of variables, it has the advantage of analyzing the properties of the dependence structure between variables in consideration of extreme events. Meanwhile, the problem is that uncertainty is a variable that is difficult to capture directly. Moreover, Bollen, Gray, and Whaley (2000) study's study indicates that the regime-switching model captures exchange rate dynamics better than the alternative time-series models. Most of the current studies analyzed crude oil prices only, and they did not include oil prices in EPU and changes in market conditions on the relationships between these variables. Most researchers find somewhat conflicting results that do not allow the researchers to conclude. Aloui, Aïssaa, and Nguyen (2013) and Ding and Vo (2012) show that increases in oil prices are correlated with the appreciation of the US dollar, but Narayan, Narayan, and Prasad (2008) and Zhang, Fan, Tsai, and Wei (2008) report a negative correlation between US dollar exchange rates and oil prices.

However, this study includes crude oil prices, US EPU, and exchange rates for five currencies. Our study contributes to the literature by examining the relationships between global oil prices (WTI) and the exchange rate of the U.S. dollar against foreign currencies (EX) by considering the effects of the U.S. EUP. We believe our findings contribute to several areas covered by modern economic research. More specifically, this study contributes to a better understanding of how changes in international oil prices are transmitted to the dollar's exchange rates. According to Arouri, Jouini, and Nguyen (2011), these findings contribute to an understanding of forecasting changes in oil prices and exchange rates, profitable oil and currency hedging, and the creation of investment strategies. Al-Abri (2013) examines whether real exchange rate responses differ according to the exchange rate regimes of some OECD (oil importers) and that the flexible exchange rate regime shows a relatively faster adjustment to its long-term equilibrium.

Methods

Our data consist of monthly statistics on WTI crude oil prices (OILP) dollars per barrel and the USD exchange rate against five currencies Canadian Dollar (CAD), Euro (EUR), British Pound (GBP), Japanese Yen (JPY), and Libyan Dinar (LYD), and the U.S. economic policy uncertainty (EPU) index proposed byBaker et al. (2016). The data covers the monthly period from January 2006 to August 2020. All the variables: oil prices, uncertainty index, and exchange rates for the five currencies were obtained from the Federal Reserve Bank of St. Louis database (FRED): https://fred.stlouisfed.org/. We chose this period to study the relationships between variables over different periods of stability and instability. Moreover, the US EPU index is based on newspapers in the US (see Baker et al., 2016). All monthly variables are expressed in natural logarithms after taking the first differences to remove heterogeneity. Table 1 shows the descriptive statistics and standard tests for these variables.

Table 1. Descriptive Statistics

	CAD	EUR	GBP	JPY	LYD	OILP	EPU
Mean	0.001	0.000	0.001	-0.001	0.000	-0.002	0.009
Std. Dev.	0.028	0.028	0.026	0.026	0.016	0.116	0.270
Skewness	0.477	0.436	0.418	0.277	2.564	-0.935	0.776
Kurtosis	5.867	4.957	4.860	4.073	21.254	10.653	5.263
J-B	66.97[a]	33.68[a]	30.54[a]	10.71[a]	2636.6[a]	455.2[a]	55.26[a]
ADF	-14.57[a]	-13.72[a]	-12.33[a]	-12.21[a]	-14.19[a]	-9.71[a]	-11.53[a]
PP	-14.55[a]	-13.71[a]	-12.45[a]	-12.21[a]	-14.19[a]	-9.28[a]	-17.17[a]
Corr. WTI	-0.30[a]	-0.23[a]	-0.31[a]	0.08	-0.24[a]	1.00	-0.31[a]
Corr. EPU	0.09	0.08	0.0.11	-0.24[a]	0.06	-0.31[a]	1.00

Notes: [a] indicate the rejection of the null hypothesis of associated statistical tests at the 1% level. Unit root tests are at constant, linear trend based on AIC. All the variables are in logarithm after taking the first differences form that we previously calculated. J-B is Jarque-Bera. Corr. refers to the correlation coefficients.

According to descriptive statistics in Table 1, the value of the standard deviation "indicator of volatility" of the EPU experienced relatively higher volatility than that of crude oil price and exchange rates during the study period. We note that the CAD and EUR are similar in terms of volatility (0.005%), and the LYD is the lowest rate of fluctuation among the exchange rates of the rest of the concerned currencies. Additionally, we note that the skewness coefficients are negative for CAD, EUR, and JPY while positive for the GBP, LYD, OILP, and EPU. Kurtosis coefficients for all variables are more significant than three. However, the Jarque–Bera test statistics, the departure from the normality test was confirmed. Finally, unit root tests by the Dickey and Fuller (1979) and Phillips and Perron (1988) tests show that all variables are stationary at their levels I(0) and significant at 1%. In addition, we found the unconditional correlation between the economic policy uncertainty index and crude oil prices. It varies significantly across the exchange rates: from -0.30 (CAD) to 0.18 (JPY) for oil prices, as shown in the penultimate row of Table 1. While the relationship between the EPU and other indicators ranges from -0.03 LYD to 0.04 (GBP) as indicated in the last row of Table 1, however, on average, the values are weak between positive and negative.

Markov Switching -VAR model

In this study, we focus on the famous Markov regime-switching approach based on Hamilton (1989, 1990) applied to exchange rates, which many economists have used to model the nonlinear behavior of economic variables such as time series jump/break (Chen, Zhu, & Zhong, 2019; Fallahi, 2011; Krolzig, 2013). Hansen (2001) and Perron (2006) also emphasized the need to consider structural and regime changes in the time-series models of the macroeconomic. Hamilton (1989) and Krolzig (2013) overcome the shortcomings of linear models dealing with asymmetry by combining MS and VAR. Therefore, our study employs the MS-VAR approach to characterize the nonlinear relationships between the respective time series. Our study aims to describe the effects of oil prices on the exchange rate of the USD against five currencies by looking at the effects of the EPU.

Equation (1) describes the autoregressive model that is the basis for time series analysis.

$$y_t = v_t(s_t) + A_1(s_t)y_{t-1} + \cdots + A_p(s_t)y_{t-p} + u_t(s_t) \tag{1}$$

Where $y_t = (y_{1t}, y_{2t}, y_{3t})'$, $t = 1, \dots, T$, s_t denotes the regime variable, with $u_t \sim NID(0, \sum(s_t))$; $v_t(s_t), A_1(s_t), \dots, A_p(s_t)$ are mean parameters related to the state variable; describe the dependence of the parameters on the realized regime s_t. $s_t = \{1, \dots, m\}$ is specified by the transition probabilities.

$$\text{Prod}(s_{t+1} = j | s_t = i) = P_{ij}, \sum_{j=1}^{m} P_{ij} = 1\, were\ i, j = 1, \dots, m\, ;\, 0 \leq P_{ij} \leq 1 \tag{2}$$

Each parameter of the model depends on the regime in which the regime is at date t. Therefore, each regime features its own shock diffusion regime.
The transition matrix P defines the transition probabilities.

$$P = \begin{bmatrix} P_{11} & P_{12} & \cdots & P_{1m} \\ P_{21} & P_{22} & \dots & P_{2m} \\ \vdots & \dots & \ddots & \vdots \\ P_{m1} & P_{m2} & \cdots & P_{mm} \end{bmatrix} \tag{3}$$

In addition, probabilities of transition on important information about the expected duration (D_j) and that the regime will stay in a certain regime (j) as in the Equation 4:

$$E(D_j) = \frac{1}{1-P_{ij}}\ , j = 1,2, \dots, m \tag{4}$$

We compute impulse response functions (IRFs) for both regime switching, oil price shock, and uncertainty occurring in a given regime based on the MS-VAR model. Koop et al. (1996) introduced regime-dependent IRFs, which can measure the responses of the regime to shocks to the variables in period h as follows:

$$IR_{\nabla u}(h) = E[y_{t+h} | \xi_t, u_t + \nabla_u;\ Y_{t-1}] - E[y_{t+h} | \xi_t, u_t;\ Y_{t-1}] \quad 5)$$

where ∇_u is the shock at time t and the responses to shocks, as in the linear VAR process:

$$IR_{uk}(h) = \frac{\partial E[y_{t+h} | \xi_t, u_t;\ Y_{t-1}]}{\partial u_{kt}} \tag{6}$$

The responses to a regime switching are defined in the spirit of the IRF concept:

$$IR_{\nabla u}(h) = E[y_{t+h} | \xi_t + \nabla\xi, u_t;\ Y_{t-1}] - E[y_{t+h} | \xi_t, u_t;\ Y_{t-1}] \tag{7}$$

where $\nabla\xi$ is the switching in regime at time t.

Results and Discussion

Nonlinearity Test

The Brock–Dechert–Scheinkman (BDS) test suggested by Broock, Scheinkman, Dechert, and LeBaron (1996) is used to test the null hypothesis of linearity and has high power against numerous nonlinear alternatives. The results of the BDS tests, as in Table 2, show the linear dependencies in the VAR residual, and the majority of the statistics are significant nonlinear dependencies. Therefore, we reject the null hypothesis of linearity. Specifically, linear dependencies occur in all variables at the 1% significance level.

Table 2. BDS Test Results.

Dimension of Embedding (m)	BDS Statistic				
	m=2	m=3	m=4	m=5	m=6
OIL	0.049***	0.078***	0.088***	0.085***	0.076***
USD/CAD	0.016***	0.021**	0.021*	0.022*	0.021*
USD/EUR	0.007	0.025**	0.034***	0.040***	0.044***
USD/GBP	0.002**	0.000	0.000***	0.000***	0.000***
USD/JPY	0.004	0.020**	0.028**	0.031**	0.028**
USD/LYD	0.002*	0.001**	0.000**	0.000	0.000
EPU	0.007	0.025**	0.034***	0.040***	0.044***

Note: ***, **, and * denote the significance of nonlinear dependency at 1%, 5% and 10% levels, respectively.

Within the scope of the study, firstly, we define the appropriate model to create a suitable MS-VAR model. In the linear VAR (p) model, the p degree was determined using the Akaike Information Criterion (AIC), Schwarz Criterion (S.C.), and Hannan-Quinn Criterion (H.Q.). Moreover, MS-VAR determination differs according to regime numbers (q) and variance matrix definition. In this regard, the appropriate model is the MS(3)-VAR(1) model. In this regard, Stillwagon and Sullivan (2020) confirmed that it is advisable to allow and test for greater than two regimes in characterizing exchange rates. After we determined the MS-VAR model, the model used Likelihood-ratio (L.R.) statistics to test the MS(3)-VAR(1) model. To test the stability of the VAR model, we determine the lag number of the VAR models using the information criteria (AIC, SC, H.Q.). The best lag number of these models is one lag.

Regime-Switching Analysis

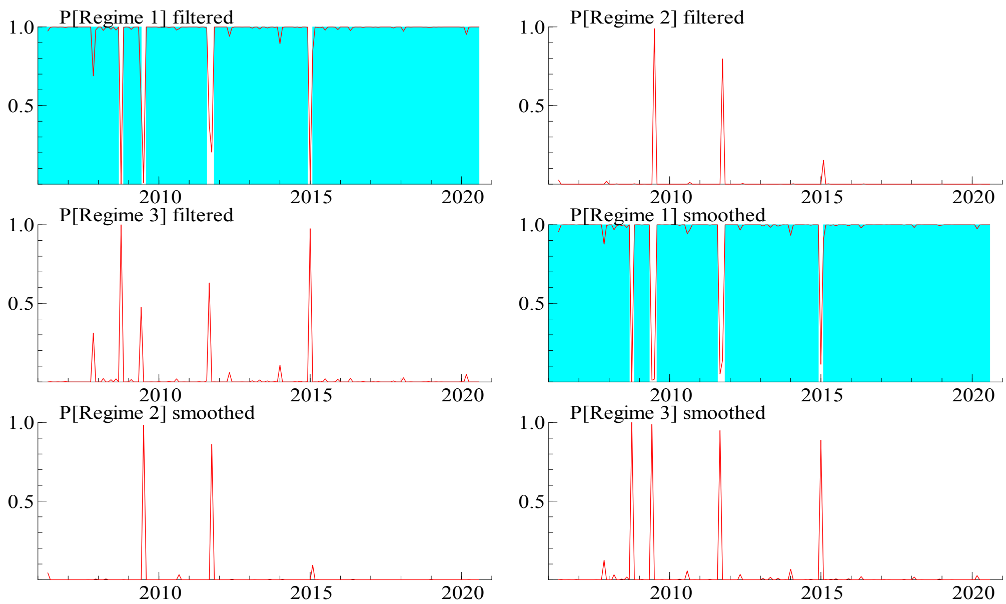

Figure 2. Filtered and smoothed probabilities for USD/CAD

According to Calvet and Fisher (2008), filtered probabilities are useful for prediction, while smoothed probabilities allow most information after data analysis. In particular, as in Figures 2 to 6, the results of the filtered and smoothed probabilities show the characteristics of the regime-switching associated with fluctuations in the exchange rates of five currencies from January 2006 to August 2020. In this context, it shows that the changes in exchange rates show a dynamic exchange regime that can be described in regime 1 "sharp decline", in regime 2 "small drop" and in regime 3 "steady rise".

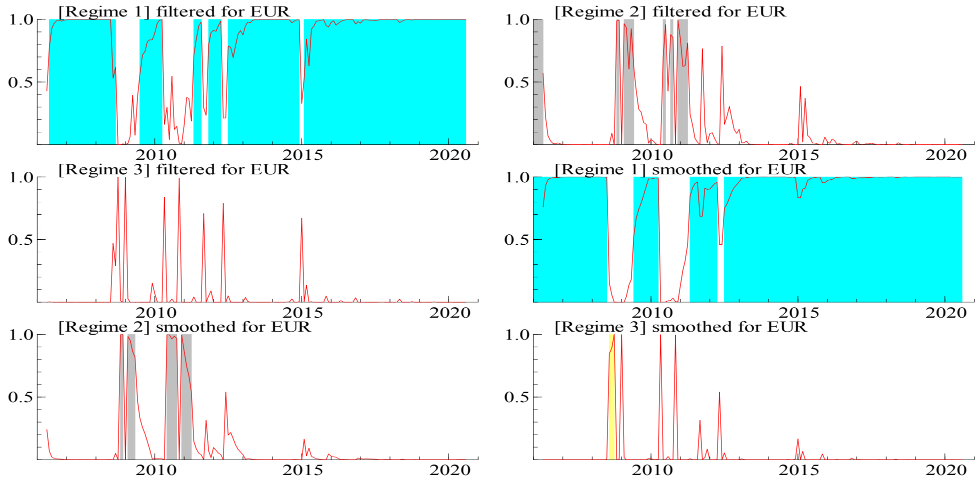

Figure 3. Filtered and smoothed probabilities for USD/EUR.

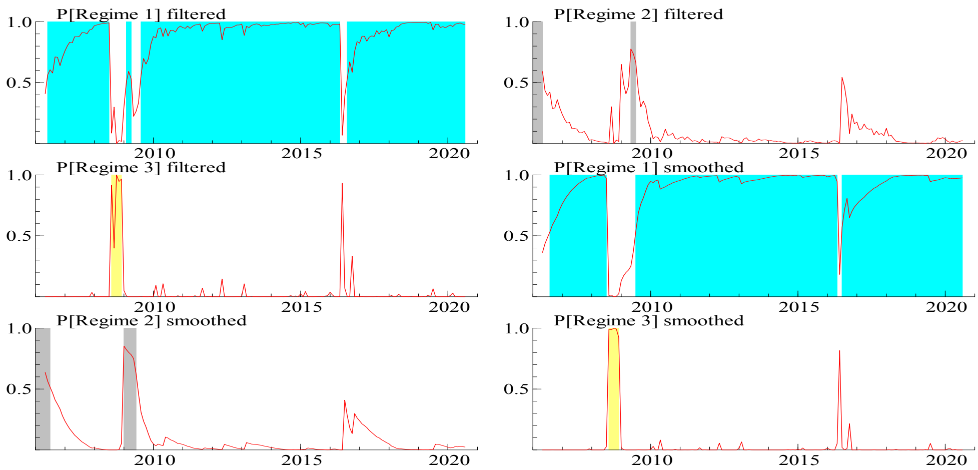

Figure 4. Filtered and smoothed probabilities for USD/GBP

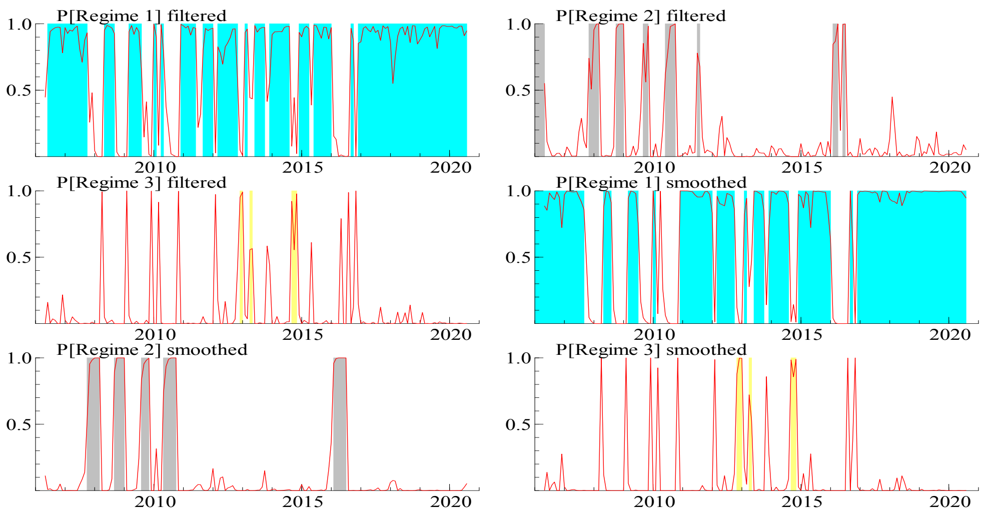

Figure 5. Filtered and smoothed probabilities for USD/JPY

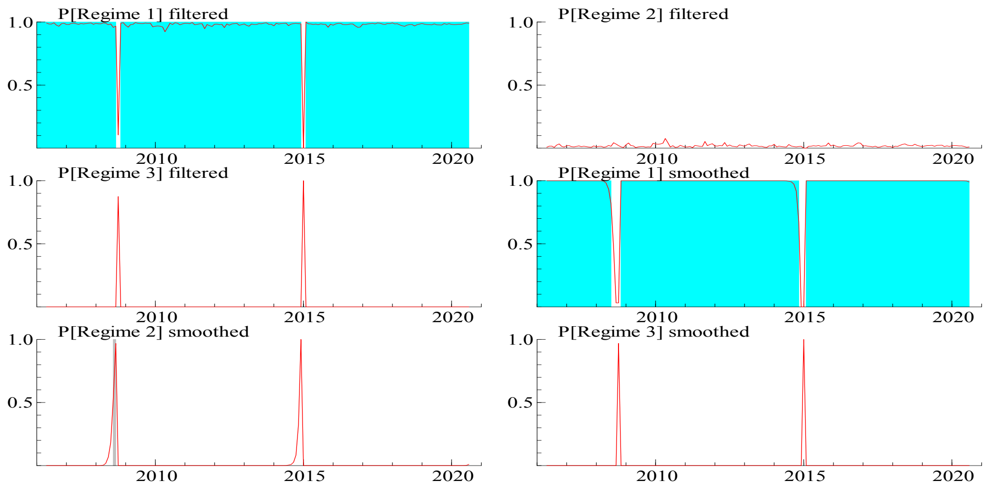

Figure 6. Filtered and smoothed probabilities for USD/LYD

Table 3 shows the transition probabilities between the three different regimes in the CAD, ERU, GBP, JPY, and LYD cases. The probability of staying in a sharp decline is 0.973, 0.978, 0.983, 0.891, 0.988, respectively; the probability of a transition from a sharp decline to a small drop regime is 0.000 in the CAD, EPU, GBP, (0.050 in case of JPY) and (0.011in case of LYD) and to a steady rise regime is 0.026, 0.021, 0.016, 0.058 and 0.000, respectively. In addition, the probability of remaining in a small drop regime is 0.000, 0.704, 0.856, 0.782 and 0.387 respectively; the probability of a transition from a small drop regime to a sharp decline regime is 1.000, 0.177, 0.143, 0.217 and 0.000, respectively and to a steady rise regime is 0.000, 0.119, 0.000 and 0.612, respectively. The probability of remaining in a steady rise regime is 0.000, 0.239, 0.608, 0.275, and 0.000, respectively. Moreover, the probability of the steady rise regime transitioning to a sharp decline regime and a small drop regime is (0.560 to 0.439), (0.000 to.0.239), (0.103 to 0.287), (0.724 to 0.000), and (1.000 to 0.000), respectively.

These findings imply that a small drop regime in the CAD and a sharp decline regime in ERU, GBP, and JPY have the highest continuous probability and, therefore, the most substantial stability. In the case of the LYD, These results indicate that the steady rise regime in LYD has the higher continuous probability and, accordingly, the strongest stability.

Table 3. Regime Transition Probabilities.

	Regime 1	Regime 2	Regime 3
Model 1(USD/CAD)			
Regime 1	0.974	0.000	0.026
Regime 2	1.000	0.000	0.000
Regime 3	0.560	0.440	0.000
Model 2(USD/EUR)			
Regime 1	0.979	0.000	0.021
Regime 2	0.177	0.704	0.119
Regime 3	0.000	0.761	0.239
Model 3(USD/GBP)			
Regime 1	0.983	0.000	0.017
Regime 2	0.143	0.857	0.000
Regime 3	0.104	0.288	0.609
Model 4(USD/JPY)			
Regime 1	0.892	0.050	0.058
Regime 2	0.000	0.782	0.218
Regime 3	0.724	0.000	0.276
Model 5(USD/LYD)			
Regime 1	0.988	0.012	0.000
Regime 2	0.000	0.388	0.612
Regime 3	1.000	0.000	0.000

After briefly explaining the characteristics of the three regimes, the study calculates regime transition probabilities to have information about the transitions between regimes. The results are shown in Table 4. First, regarding the CAD regimes, the result shows that a small drop regime and a steady rise regime tend to last for one month for both regimes on average, representing 1.16% and 2.33% of the sample, respectively. However, regime 1 is also the most stable, representing 96.51% of the sample and an average of 33.20 months. Second, concerning the EUR regimes, Table 4 shows that a small drop regime and a steady rise regime tend to last for 3.40 months and 1.40 months on average, representing 9.88% and 4.07% of the sample, respectively. We also find that a sharp decline regime is also the most stable, representing 86.05% of the sample and an average of 37 months.

Third, Table 4 related to the GBP regimes shows that a case of small decline regime and steady rise regime tends to last for 4.50 months and 3.00 months on average, representing 5.23% and 3.49% of the sample, respectively. The sharp decline regime is the most stable, accounting for 91.28% of the sample, with an average of 52.33 months. Fourth, in the aspect related to the JPY regimes, it appears that the case of small decline regime and steady rise regime tends to last for 5.40 months and 1.42 months on average, representing 15.70% and 9.88% of the sample, respectively. The sharp decline regime is the most stable, accounting for 74.42% of the sample, with an average of 9.85 months. Fifth, Table 4, related to the LYD regimes, shows that a case of small decline regime and steady rise regime tends to last for 1.50 months and 1.00 months on average, representing 1.74% and 1.16% of the sample, respectively. Furthermore, the sharp decline regime is the most stable, accounting for 97.09% of the sample, with an average of 55.67 months. In addition, the volatility is higher for regime 1 than for regimes 2 and 3. In general, the sharp decline regime is the most stable, representing between 74.42% and 97.09% of the sample.

Table 4. Information on Regime Structure.

	Number of samples	Probability	Duration
Model 1(USD/CAD)			
Regime 1	166	0.965	33.20
Regime 2	2	0.012	1.00
Regime 3	4	0.023	1.00
Model 2(USD/EUR)			
Regime 1	148	0.861	37.00
Regime 2	17	0.099	3.40
Regime 3	7	0.041	1.40
Model 3(USD/GBP)			
Regime 1	157	0.913	52.33
Regime 2	9	0.052	4.50
Regime 3	6	0.035	3.00
Model 4(USD/JPY)			
Regime 1	128	0.744	9.85
Regime 2	27	0.157	5.40
Regime 3	17	0.099	1.42
Model 5(USD/LYD)			
Regime 1	167	0.971	55.67
Regime 2	3	0.017	1.50
Regime 3	2	0.012	1.00

Effects of Oil Shocks

Table 5 shows the effect of oil prices and EPU on exchange rates. In the first system, the sharp decline regime, we found a statistically significant negative impact of oil prices and EPU on the CAD. Thus, CAD and EPU can be helpful in forecasting changes in oil prices during periods of high volatility ((Roubaud & Arouri, 2018). There is a negative effect of EPU on the CAD in the third system, i.e., a 1% increase in EPU leads to a 0.14% increase in CAD. This result means that the foreign exchange market experiences tremendous pressure during periods of high uncertainty and remains relatively calm when uncertainty is low. This negative effect of uncertainty on exchange rates is consistent with Krol (2014) and Kido (2016), which showed that high EPU leads to higher exchange rate volatility.

In addition, concerning the impact of oil prices and EPU on the EUR, we find a positive effect of the oil price on the EUR in the sharp decline regime. Specifically, a 1% increase in oil prices causes the EUR to rise by 0.27%. This finding is consistent with Juhro and Phan (2018), where they found that EPU positively and statistically predicts the exchange rates of six out of ten ASEAN currencies. Moreover, this is consistent with Roubaud and Arouri (2018) findings that EPU depends on previous changes in oil prices. EPU dynamics seemingly persist to a degree, and this persistence is stronger during high volatility periods. In contrast, there is a statistically significant negative effect of oil price on the USD/EUR in the third regime, where an increase in the oil price by 1% leads to a decrease in the EUR by 0.8%. This finding is consistent with Roubaud and Arouri's (2018) findings that the exchange rate, stock markets and EPU are not correlated with oil prices in a low volatility regime. However, there was no statistically significant effect in the second regime - the small drop regime. On the one hand, the impact of the oil price and the EPU on the GBP, in the case of the sharp decline regime, we find that there is a negative effect of the oil price on the GBP. In addition, an increase in the oil price by one unit leads to a decrease in the GBP by 0.5%, while there is no statistically significant effect of the EPU on the GBP.

Moreover, Table 4 show a statistically significant effect of the EPU on JPY in the third regime, as an increase in EPU by one unit will lead to a rise in the exchange rate by 0.13%. However, there is a negative impact of the oil price on JPY for both the second and third regimes, but its influence in the small drop regime is more than its influence in the third regime. In the case of Libya, there is no statistically significant effect of the oil price and the EPU on the LYD. Our results are consistent with, Lizardo and Mollick's (2010) study which find that an increase in the real oil price leads to a depreciation of the U.S. dollar against the currencies of oil exporters.

Generally, the impact of the oil price is more significant than the effect of EPU on the exchange rate of these currencies, which is in line with a study of Aimer (2021). We also find that most of the effects of the oil price were negative, while most of the impact of the EPU on the exchange rate were positive. In addition, there is no effect of the EPU on the EUR, GBP, and LYD.

Table 5. Regression Coefficients of Regime Transition.

	Regime 1	Regime 2	Regime 3
Model1	CAD_t	CAD_t	CAD_t
EPU_{t-1}	-0.006**	-0.010	0.136***
OIL_{t-1}	-0.054*	-0.046	-0.138
Model2	EUR_t	EUR_t	EUR_t
EPU_{t-1}	-0.017	0.019	-0.008
OIL_{t-1}	0.272***	0.004	-0.081*
Model3	GBP_t	GBP_t	GBP_t
EPU_{t-1}	0.013	0.020	-0.054
OIL_{t-1}	-0.052*	-0.004	0.083
Model4	JPY_t	JPY_t	JPY_t
EPU_{t-1}	-0.014	-0.012	0.131***
OIL_{t-1}	-0.039	-0.068*	-0.018
Model5	LYD_t	LYD_t	LYD_t
EPU_{t-1}	-0.007	0.001	0.074
OIL_{t-1}	0.003	-0.017	-0.434

Note: ***, **, and * denote significance at the 1%, 5%, and 10% level of significance, respectively.

Impulse-Response Functions

For further analysis, we use the cumulative impulse response by MS (3)-VAR (1) to investigate the direction and duration of the effects of oil prices on exchange rates by considering the effects of EPU. We observe the cumulative response to the exchange rates of the three regimes over a 10-month horizon, as shown in Figures from 7 to 11.

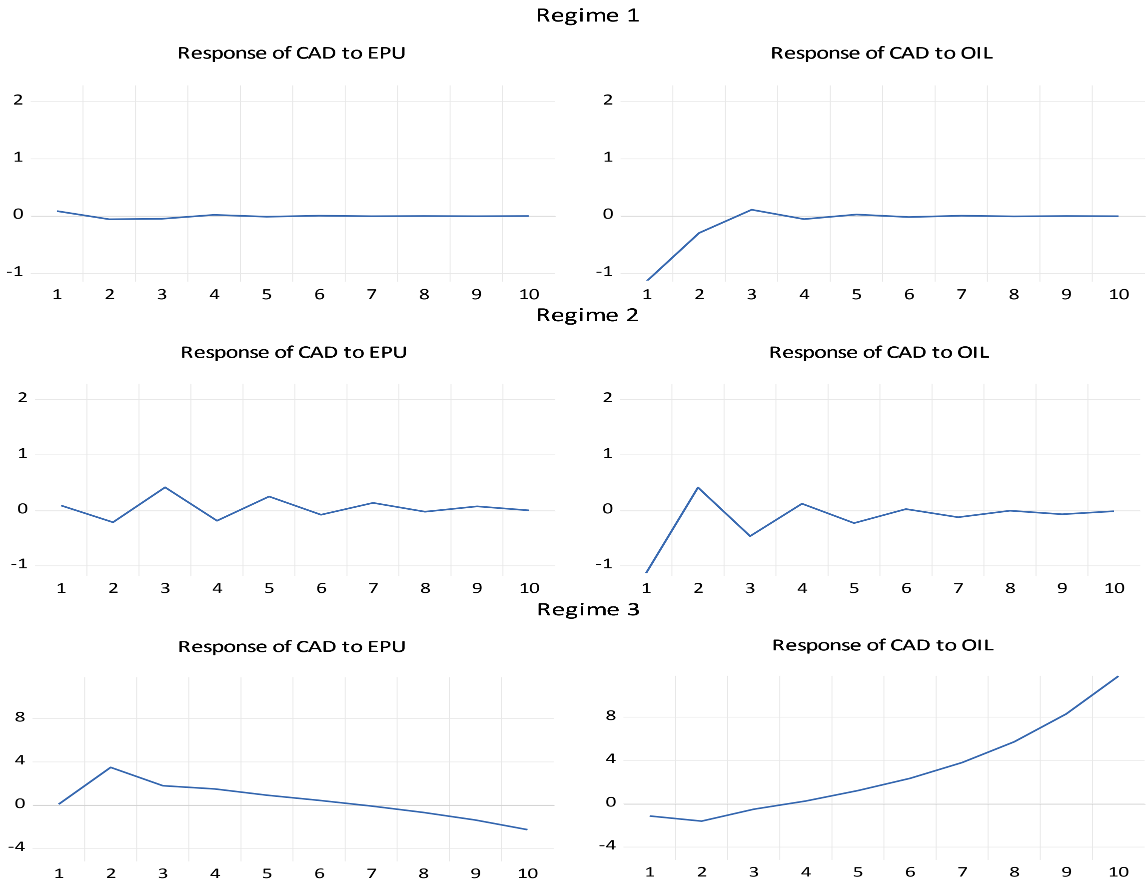

Figure 7. Impulse response of USD/CAD

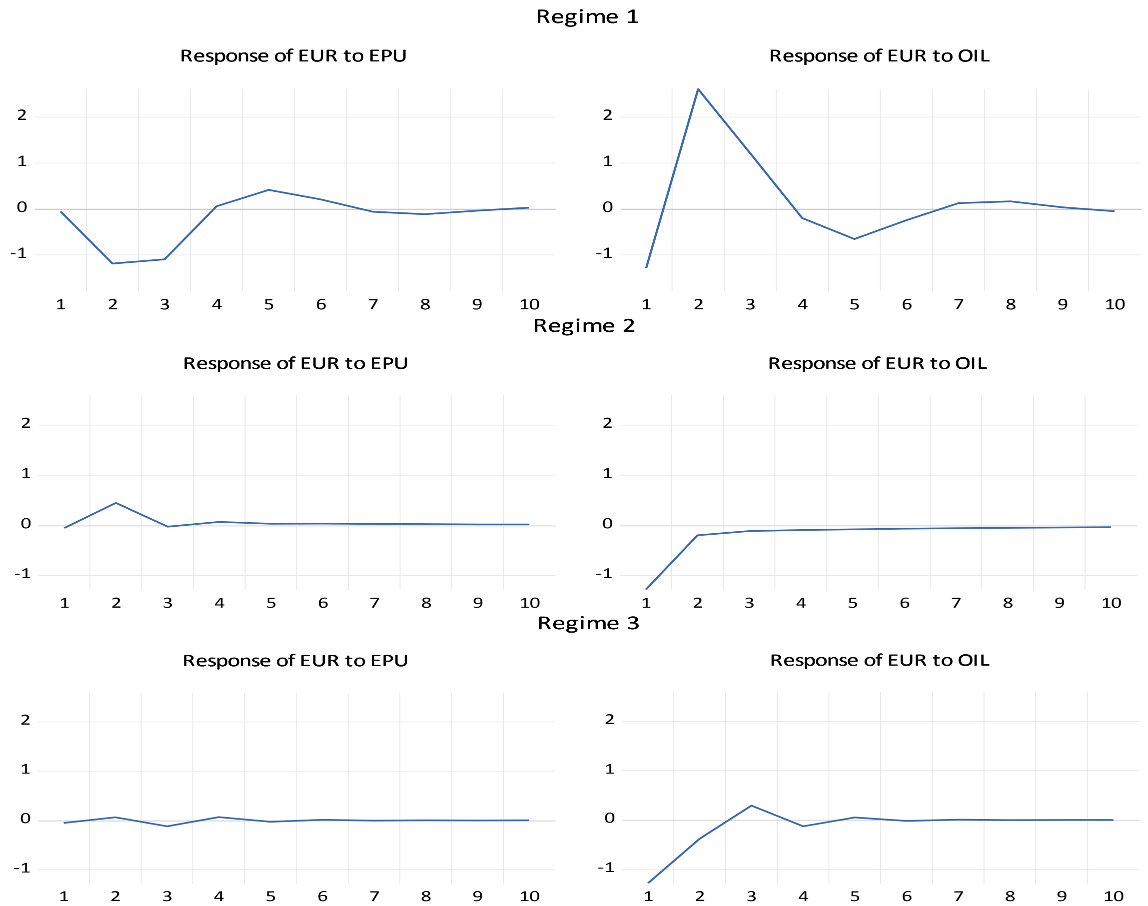

Figure 8. Impulse response of USD/EUR

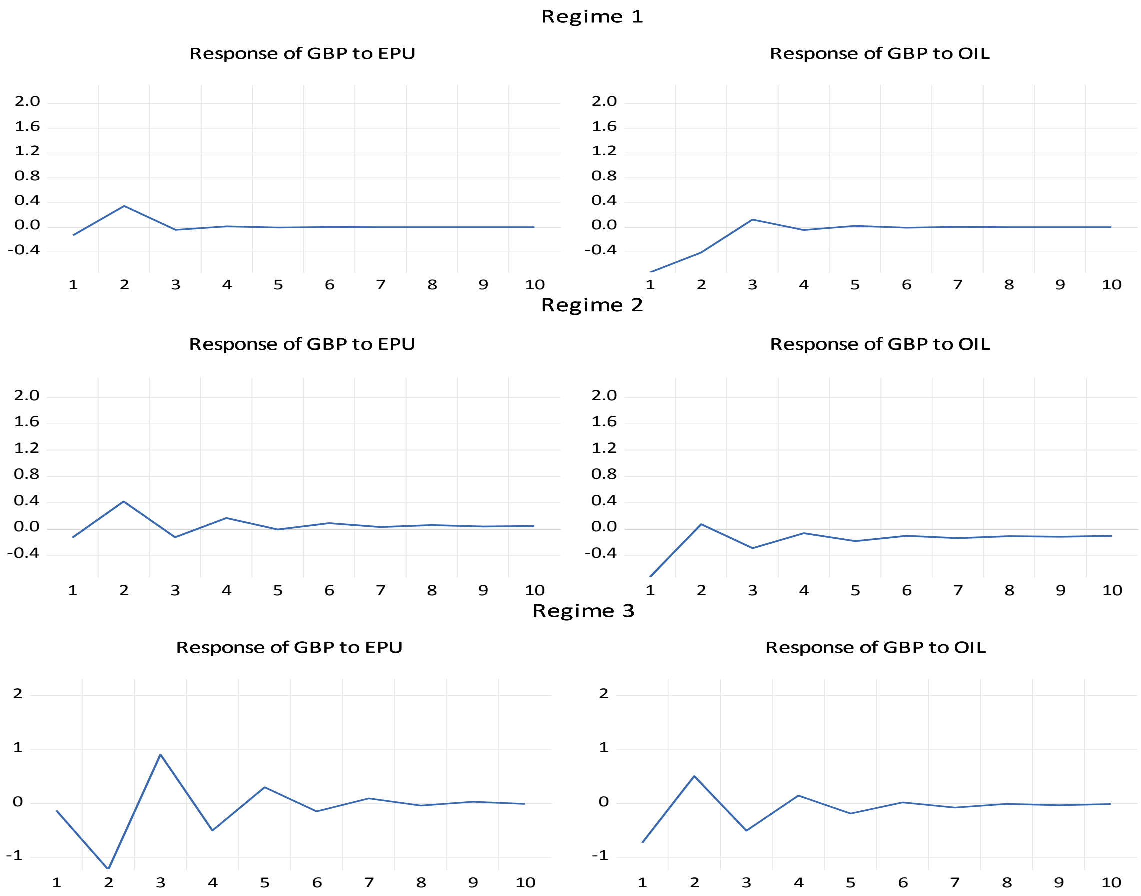

Figure 9. Impulse response of USD/GBP

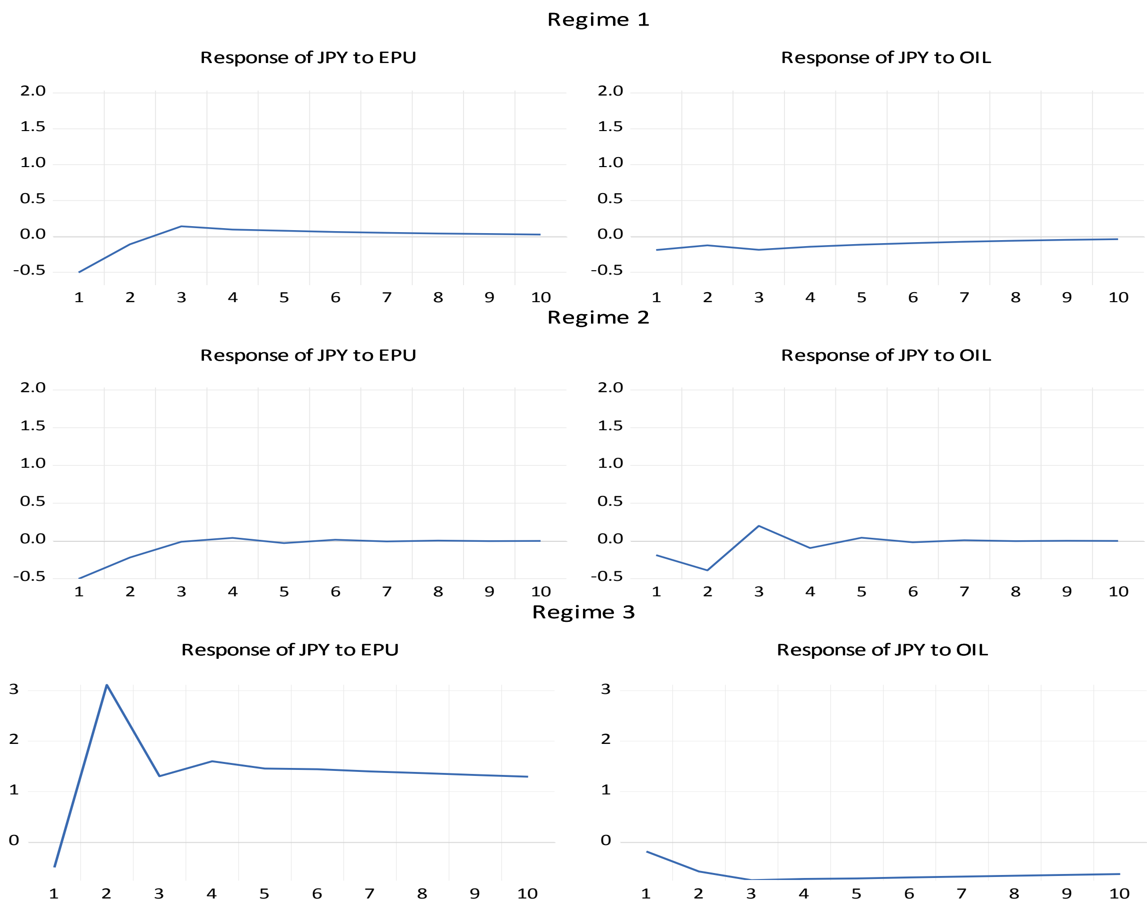

Figure 10. Impulse response of USD/JPY

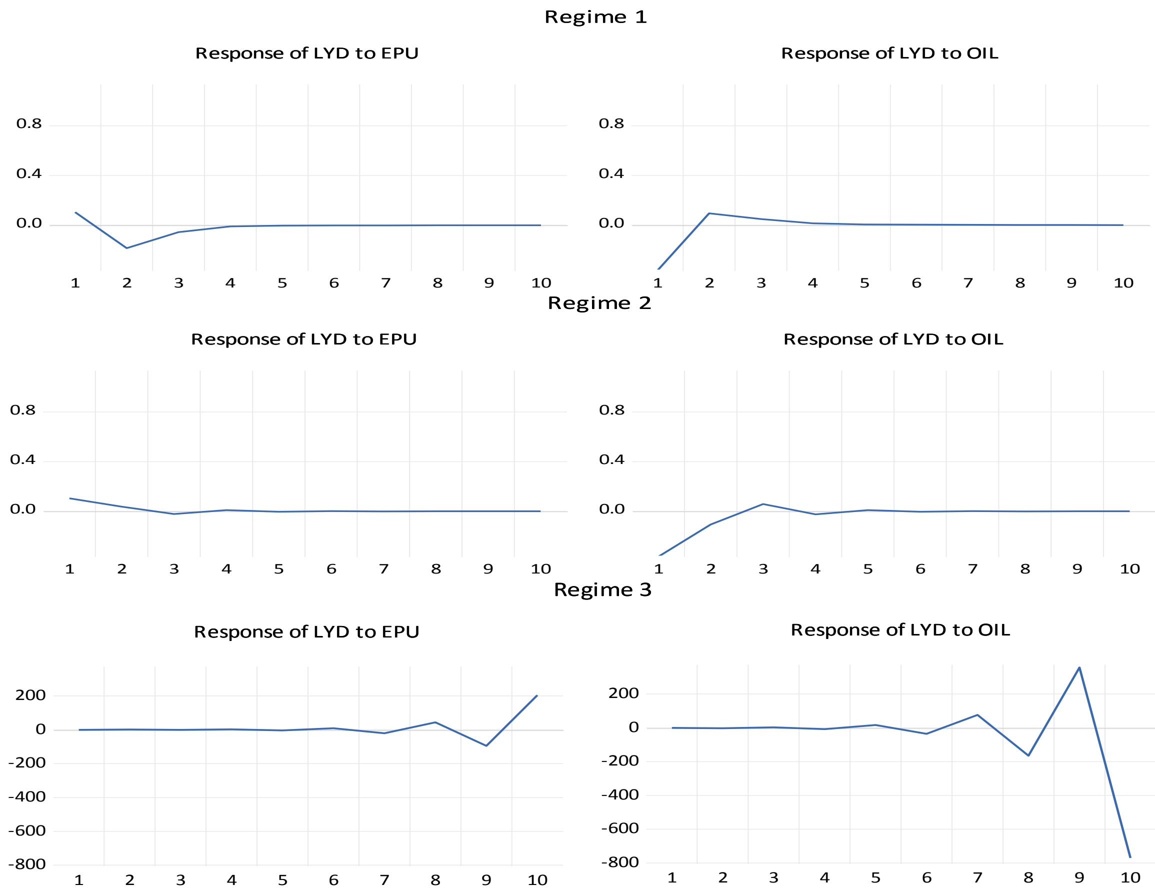

Figure 11. Impulse response of USD/LYD

As shown in Figure 7, the EPU shock causes a slight response between positive and negative for the CAD in the first system. In the first and second regimes, the shock effect is minor, fluctuating between positive and negative without an obvious pattern until the end of the period. In the third regime, the EPU shock had positive and negative effects until the middle of the sixth month and peaked at (3.48) in the second month, after which its effect faded.

Concerning the impact of the oil price shock on the CAD, in the first regime, the effect of the shock is negative during the first trimester, and its effect disappears after the third month. In the second regime, the impact of the shock fluctuates between negative and positive until the middle of the seventh month, after which it is minimal. In the case of the steady rise regime, the impact of the shock is negative until the third month, and then the effect becomes increasingly positive, reaching a peak of 11.79 at the end of the period. In particular, the impact of the shock of EPU and the oil price shock on the CAD differs between the three regimes.

Second, the dynamic effect of the EUR response from the uncertainty shock is shown in Figure 8. In the first regime, the results show that the oil price variable appears to have significant impacts during the first four months. However, the shock to the EPU led to an increasingly negative response in the euro exchange rate during the first and second months. Then the response changes to positive during the fourth month until its effect stabilizes after the fourth month. While in regime 2, the response is positive during the first three months; after that, its effect fades away until the end of the period.

In the case of the steady rise regime, the impact of the shock is slight, between negative and positive, until its effect fades after the sixth month. There is a sudden negative to positive euro exchange rate response in the first four months in the first regime. It is negative, peaking at -1.28 in the first month, and its positive peak at (2.60) in the second month, after which its effect becomes minor. In the second and third regimes, there is a diminishing negative effect over the length of the period.

Third, the dynamic effect of the GBP response to the EPU shock, as shown in Figure 9. In regimes 1 and 2, the EPU shock and the oil price shock lead to a negative exchange rate response during the first month and then change to positive during the first three months to that their effect fades. While in the third regime, there is a surprising fluctuating effect between negative and positive of the shock of EPU on GBP during the first seven months. We find that the impact of a shock in the first and second regimes is different from the third. In addition, the effect of the oil price shock on the exchange rate is similar between the three regimes, as the effect fluctuates during the first six months, and after that, the effect fades.

Fourth is the perspective of the dynamic impact of the JPY with response to the EPU shock (Figure 10). In regimes 1 and 2, there is a sudden effect of negative to positive due to the shock of EPU during the first three months and after the third month; it becomes a long-lasting positive effect of EPU shock. Regarding the exchange rate response to the oil price shock, there is a negative and diminishing effect in the first regime, which fades away at the end of the period. While in the second regime, there is a fluctuating effect between negative and positive until the first six months, and then their effect fades. Finally, in the third regime, there is a negative impact of trauma over the period.

Fifth is the dynamic effect of the LYD response (Figure 11). In the case of the first regime, the impact of the EPU shock leads to a positive response in the LYD during the first month and then turns negative in the second and third months. After that, its effect wanes until the tenth month. In the second regime, the impact of the shock is positive during the first three months, and after that, its effect diminishes until the tenth month. In the case of the third regime, there is no effect of the shock during the first seven months, after which the effect fluctuates between positive and negative without an obvious pattern. Likewise, in the first and second regimes, the shock in oil price leads to a negative response during the first two months, after which its effect diminishes. While in the third regime, the oil price shock has no effect on the exchange rate during the first six months, its impact becomes surprising between positive and negative.

In the short term, we found that the effect of the crude oil price on most exchange rates is negative, but the degrees of response between them vary. Likewise, in the long term, the impulse responses of most exchange rates converge to zero, except for the response of the CAD and LYD in the case of the third regime. On the other hand, there is no evidence to classify the impact of EPU shocks on exchange rates in the short and long term. This result confirms that the importance of lagged exchange rates varies by the regime ((Basher, Haug, & Sadorsky, 2016).

In comparison with previous studies related to our research, our results differ from earlier studies due to the different exchange rate regimes and the diversity of countries' economies in terms of whether they are exporters or importers of oil. Our findings are of great importance to policymakers and investors regarding managing exchange rate fluctuations and preventing potential risks that may arise due to heavy reliance between different markets.

Conclusion

This paper contributes to previous studies on the interactions between oil prices and exchange rates by considering the effects of EPU. Based on the M.S. -VAR model. The transition probabilities between the three different regimes show that the small drop regime in the CAD has the highest continuous probability and, accordingly, the strongest stability. While the sharp decline regime in the EUR, the GBP, and JPY have the highest continuous probability, so these currencies have the strongest stability. Otherwise, the steady rise in the LYD has the higher continuous probability, and accordingly, the strongest stability. Overall, a sharp decline regime is the most stable, representing between 74.42% and 97.09% of the sample.

In terms of the effect of exchange rates and EPU on the relevant exchange rates, we find that the impact of the oil price on the exchange rate of the concerned currencies is more significant than the effect of economic policy uncertainty on the exchange rate of these currencies. We also find that most of the effects of oil prices were negative, while the effects of EPU on the exchange rate were positive for the CAD and JPY. However, there is no effect of EPU in the EUR, GBP, and LYD.

Moreover, the results of the IRFs also showed that the effect of the oil price on most exchange rates is negative in the short term, but the degrees of response between them vary. Likewise, in the long term, the driving responses of most exchange rates converge to zero, except for the CAD and LYD in the steady rise regime.

Several future research methods are possible. First, further empirical investigations should examine whether including EPU and exchange rate changes improves oil price forecasts. Second, this study should be extended to other developed and emerging oil-exporting and importing countries to observe how exchange rates respond to oil prices and economic policy shocks.

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