

Time-varying relationship between oil price and exchange rate

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Abstract

This paper contributes to better understand the dynamic interaction between effective exchange rate (EER) and oil price for an oil-importing country like the U.S. by considering a Time-Varying Parameter VAR model with the use of monthly data from 1974 to 2017. Our findings show a depreciation after an oil price shock in the short-run for any period of time, although the pattern of long-run responses of U.S. EER is diverse across time periods, with an appreciation being observed before the mid-2000s and a depreciation afterwards. This diversity of response should lead policy makers to react differently in order to counteract such shocks. Furthermore, the reaction of oil price to an appreciation of U.S. EER is negative and different over time. Thus, the different responses may generate different adverse effects on investment and the knowledge of such effects may help financial investors to diversify their investments in order to optimize the risk-return profile of their portfolios.

Keywords. Oil price, Exchange rate, TVP-VAR model.

1 Introduction

The relationship between nominal oil price and U.S. effective exchange rate seems to change over time (see Figure 1), which is confirmed when we calculate rolling correlations between the two series (see Figure 2). It is observed that the correlation takes negative and positive values before October 1990, although the positive values predominate with the average correlation being 0.023. This

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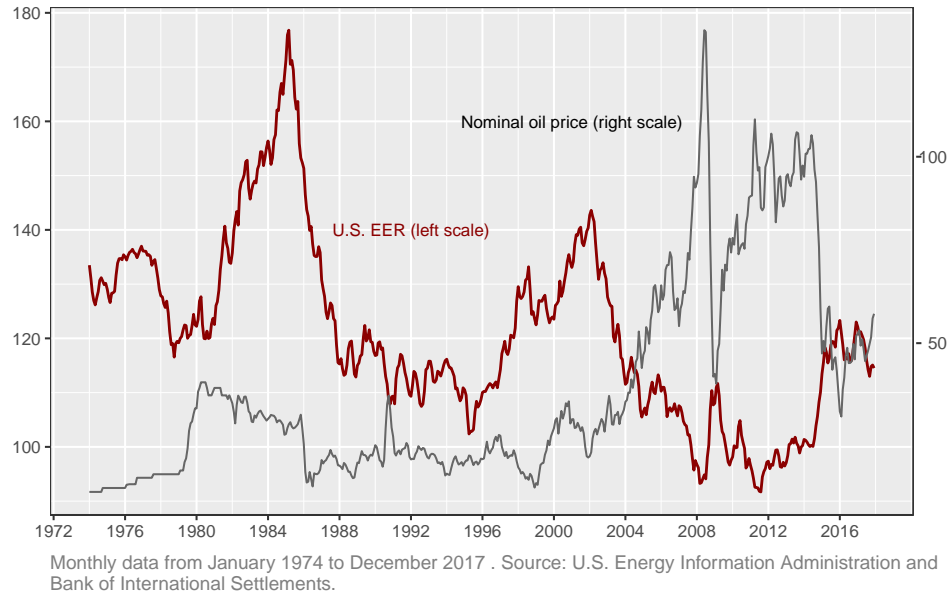


Figure 1: Nominal oil price and U.S. EER

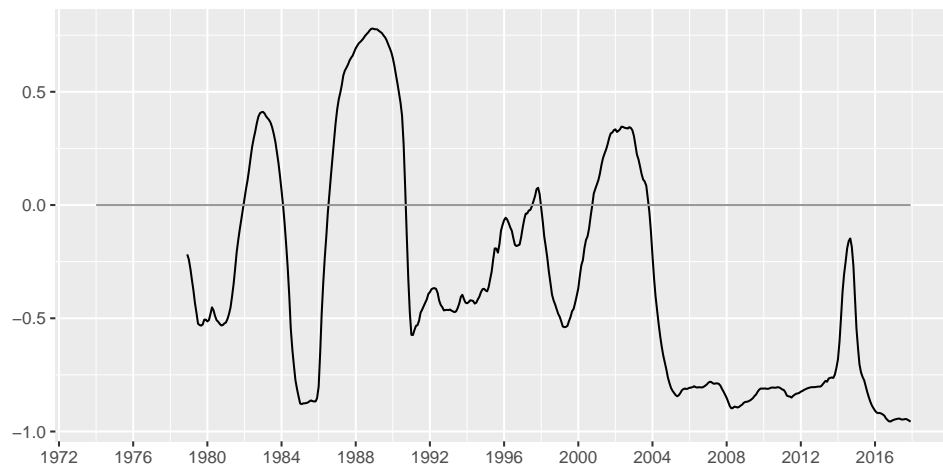


Figure 2: Five-year rolling correlation between nominal oil price and U.S. EER

period is characterized by the troubles in world oil market in the 1970s (Yom Kippur War, Iranian Revolution and Iran-Iraq War) and a subsequent relative stable oil prices disrupted by the sharp drop in the mid-1980s and the Gulf War in August 1990. The correlation between October 1990 and November 2000 is basically negative, with an average value of -0.309. In the mid-1990s there are an increase in the Iraqi production, a reduction of Asian oil demand due to the Asian crisis and an increase in world oil inventories because of warm winters. Following this period, oil price triples between January 1999 and September 2000 as a consequence of a strong global oil demand, OPEC oil production cutbacks and other factors such as low levels of oil stock and the weather. The correlation is positive, with an average value of 0.234, between December 2000 and November 2003. This period is associated with the upward trend caused by global demand in Asia and the remarkable role of oil and other raw commodities as alternative financial assets. Finally, the correlation is strongly negative from December 2003 onwards, with the average value being -0.773. In addition to the oil demand from Asia, this period is related with the sharpest drop caused by the global financial crisis in 2008, the subsequent weak global oil demand and the considerable role played by the larger global supply (especially, the U.S.). Therefore, it seems clear that the relationship between the two variables has not been the same over time and the changes in their link should be considered when we model such a relationship.

The empirical literature has analyzed the direction of the causality between oil price and exchange rate, although there is no consensus about the direction. Whereas there are studies that emphasize the role of the exchange rate anticipating the movements in oil price (see, e.g., Trehan, 1986; Yousefi and Wirjanto, 2004; Breitenfellner and Cuaresma, 2008; Zhang et al., 2008; Akram, 2009; Chen et al., 2010; Beckmann and Czudaj, 2013; Coudert and Mignon, 2016), others studies such as Amano and Van Norden (1998), Chen and Chen (2007), Lizardo and Mollick (2010), Ferraro et al. (2015) and Habib et al. (2016) focus on the reverse anticipation (i.e., oil price changes anticipate changes in exchange rates). Moreover, there are also authors that show the existence of causality in both directions (see, e.g., Wang and Wu, 2012;¹ Fratzscher et al., 2014).

The differences in the direction of the causality in the empirical evidence are related, among others, to three key issues: i) data frequency (for example, in a study for some small exporting countries, Ferraro et al., 2015, argue that commodity prices -including oil price- contain significant valuable information for predicting exchange rate at daily data, while the predictive content is weaker at monthly and quarterly frequency); ii) oil-dependence of the country (i.e., being either an oil-importing or an oil-exporting country) for each specific period of time (for instance, Ferraro et al., 2015, point out the improvement in the prediction of exchange rate by means of a forecast model including oil price after Canada became a net oil-exporting country);² and iii) period of analysis (for example, Coudert and Mignon, 2016, find a negative relationship between

¹Wang and Wu (2012) find that a unidirectional causality running from petroleum prices to exchange rates in the period before the great crisis, and a bidirectional one afterwards.

²It could depend on the relative importance of oil in the imports and exports at each time.

real oil price and U.S. real effective exchange rate when they use the monthly full sample 1974-2015, but this relationship turns positive when the sample ends in the mid-2000s).³ The latter two issues may have to do with the possible existence of structural breaks, but there is not a clear conclusion about such an existence in the related literature. Thus, Chen and Chen (2007) do not find evidence of structural breaks for G-7 countries in the relationship between oil price and real exchange rate by using monthly data from January 1972 to October 2005. However, Fratzscher et al. (2014) show evidence of structural breaks in the early 2000s by applying the Chow-type-heteroskedasticity-robust Wald-statistic for parameter instability to Granger causality regressions.⁴

From a theoretical standpoint, the literature suggests a link between oil price and exchange rate based on the source of the shock (oil price shock or exchange rate shock) and the sign of the response of the other variable to such a shock (see, e.g., Coudert and Mignon, 2016).

First, there is a negative relationship between oil prices and exchange rates, which is based on the reaction of exchange rates to changes in oil prices. The transmission mechanism through which oil prices can be transmitted to exchange rate include both the wealth (see, e.g., Golub, 1983; Krugman, 1983) and the terms of trade channels (see, e.g., Backus and Crucini, 2000; Chen and Rogoff, 2003; Cashin et al., 2004; Habib et al., 2016). On the one hand, an increase in oil prices reduces the U.S. dollar (USD) reserves in oil-importing countries and generates current account imbalances and portfolio reallocation (Bodenstein et al., 2011). Consequently, it is expected a depreciation of the domestic currency with respect to USD in oil-importing countries. On the other hand, a rise in oil prices increase import prices in relation to export prices in oil-importing countries, which causes a negative impact on the terms of trade and the depreciation of the domestic currency.

Second, there is a negative link between oil prices and exchange rates, which is based on how oil prices react to changes in exchange rates. On the one hand, oil price changes due to an increase in the attractiveness of oil and other commodities as a form of alternative asset against the fall in the price of U.S. assets and USD depreciation (the so-called financialization of the commodity markets or portfolio rebalancing argument; see, e.g., Coudert and Mignon, 2016; Breitenfellner and Cuaresma, 2008). On the other hand, oil price changes due to movements in world oil markets. On the basis of the law of one price for tradable goods, authors such as Blomberg and Harris (1995) argue that given that crude oil is an international commodity traded in USD, an appreciation of the USD increases oil price measured in terms of the domestic currency, which reduces oil demand and, consequently, oil price declines.

Third, there is a negative relationship between oil price and exchange rate

³This condition is also remarks by Lizardo and Mollick (2010) for other countries.

⁴Chen et al. (2010) analyze the Granger causality between exchange rates and commodity prices (excluding oil) in five exporting countries (Australia, Canada, Chile, New Zealand and South Africa) by using a procedure robust to potential structural breaks. They find that exchange rates have a robust power in predicting commodity prices, while the reverse Granger-causality is notably less robust.

originated by indirect channels. Thus, Coudert and Mignon (2016) highlight that the U.S. restrictive monetary policy may give rise to a USD appreciation due to higher interest rates and a decline in oil price due to lower oil demand.

Finally, there is a positive relationship between oil price and exchange rate, with exchange rates reacting to changes in oil prices on the basis of the petrodollar recycling. Specifically, after an increase in oil price, oil-exporting countries (e.g., OPEC members) increase their demand for assets nominated in USD, which pushes up the USD exchange rate (Krugman, 1983).

Therefore, the devaluation of the USD may increase world oil prices (negative relationship) for two reasons: i) a rise in oil demand in oil-importing countries and a decline in oil supply in oil-exporting countries (world oil market movements); and ii) a lower return on the USD denominated financial assets and, consequently, an increase in the attractiveness of oil and other commodities as alternative assets (portfolio rebalancing argument). On the other hand, following a rise in oil price, there is a depreciation in the exchange rate (negative relationship) due to terms of trade and wealth effects, but an appreciation (positive relationship) originated by petrodollar recycling. Finally, there could be external shocks like U.S. interest rate increases, which lead to a USD appreciation and an oil price declines.

This paper contributes to better understand the dynamic interaction between effective exchange rate and oil price for an oil-importing economy like the U.S. In doing so, we consider a Time-Varying Parameter (TVP) VAR model with monthly data from January 1974 to December 2017. Our main findings can be summarized as follows: (i) while the volatility of U.S. EER has decreased over time (with a higher average for the period before mid-1990s), the volatility of oil price has showed a sharp increase since 2000, moreover; these volatilities appear to be related with global economic and political events; (ii) the relationship between U.S. effective exchange rate and oil price before the early 2000s seems to be driven by oil price shocks, but the sharp negative link found afterwards seems to have been driven by exchange rate movements; (iii) the responses of exchange rate to oil price shocks were positive before 1990s, highlighting the importance of the petrodollar recycling during those years; however, these positive responses have been disappearing from the 1990s onwards to turn out in short-term negative responses, which can be explained by the wealth and the terms of trade channels; (iv) an appreciation of U.S. EER has always had a negative impact on the oil price; the negative short-term responses may be related with the adjustment in international oil markets, while the large long-term responses seem to be related with the remarkable role of the financialization argument since the 2000s.

The remainder of the paper is organized as follows. Section 2 describes data. Section 3 presents the methodology. Section 4 displays the results. Section 5 presents some concluding remarks.

2 Data

2.1 Data description

We consider monthly data for the nominal oil price, which is defined as the spot price of West Texas Intermediate in USD per barrel and is taken from U.S. Energy Information Administration (EIA) (<http://www.eia.gov>), and the U.S. nominal narrow effective exchange rate (EER) published by the Bank for International Settlements (<http://www.bis.org>).⁵ The sample period runs from January 1974 to December 2017, with a total number of 528 observations.⁶

2.2 Identifying shock episodes

We study the relationship between oil price and exchange rate with a special focus on shock episodes occurred for both variables. We identify nine oil price shock episodes, of which 5 are positive and 4 are negative (see Table 1).⁷ Moreover, most of the shocks characterized by larger duration and high growth rates have occurred since 2000. In fact, the longest and sharpest oil price shock episode started in December 2001. Additionally, we also identify three shock episodes related to exchange rate movements.

	Start date	End date	Months	Total growth (%)	Event
Oil price shocks					
1	Jan-79	Apr-80	16	98	Iran revolution
2	Nov-85	Mar-86	5	-89	OPEC collapse
3	Jun-90	Oct-90	5	76	Kuwait war
4	Dec-96	Dec-98	25	-81	Asian crisis
5	Jan-99	Nov-00	22	105	
6	Dec-01	Jun-08	62	194	Asian boom
7	Jul-08	Dec-08	6	-118	Great crisis
8	Jan-09	Apr-11	27	103	Global recover
9	Jun-14	Jan-16	21	-125	Weak growth
Effective exchange rate shocks					
1	Oct-78	Mar-85	51	42	US monetary policy
2	Apr-85	Apr-88	64	-45	
3	Feb-02	Jul-08	78	-42	US monetary policy

Table 1: Timing and duration of shock episodes

⁵It is worth noting that the narrow effective exchange rate comprises 27 economies, with weighting matrix for each period of time given at web page <http://www.bis.org>.

⁶Although the floating exchange rate period starts in 1973, we consider data from 1974 onwards in order to avoid the possible turbulences of the 1973 transition year. We do not consider data before 1973 due to the existence of "Bretton Woods" fixed exchange rates.

⁷Following the identification of oil price shock episodes performed by Blanchard and Galí (2010), we define a shock episode as a period that involves a cumulative change larger than 40% (positive or negative) in the log of the variable.

2.3 Granger causality

As a first step, we analyze which variable anticipates the movements of the other. In doing so, we first apply the linear Granger (G) causality test between nominal oil price (O_t) and U.S. EER (EER_t). Figure 3 shows that the null hypothesis that exchange rate does not G-cause oil price is only rejected at the 10% critical level when $p = 1$, while the reverse G-causality (from oil price to exchange rate) is never rejected. However, we are conscious that the linear test might well not capture properly the true relationship since the linear causality is not able to identify nonlinear linkage mechanism. Thus, we apply the nonlinear G-causality test proposed by Diks and Panchenko (2006) -henceforth DP- to the de-linearized series obtained by using the VAR filter, whose number of lags are 2 based on Schwarz Information Criterion. It is worth noting that "by removing linear predictive power with a VAR model, any causal linkage from one residual series of the VAR model to another can be considered as nonlinear predictive power" (see Hiemstra and Jones, 1994; Bampinas and Panagiotidis, 2015). Figure 4 shows the p -values of the DP test for 24 lags. While we cannot reject the null hypothesis that the residuals of oil price equation $\hat{\varepsilon}_t^O$ do not G-cause the residuals of EER equation $\hat{\varepsilon}_t^{EER}$, we can do it when the reverse causality is considered for lags larger than 6. Therefore, it seems that the G-causality runs from exchange rate to oil price. This allows us to consider the order $[EER_t, O_t]$ when we apply VAR models.⁸

3 Methodology

3.1 VAR model

We analyze the relationship between oil price and exchange rate by using a TVP-VAR model. However, we first estimate a VAR (time-invariant) model in order to provide a comparative perspective. Specifically, the reduced form is written as

$$y_t = a + \sum_{j=1}^p \Phi(p)y_{t-j} + u_t \quad (1)$$

with y_t being a (2×1) vector that contains the U.S. EER and the nominal oil price,⁹ and with u_t being a generalization of a white noise process with

⁸We are conscious that the order of the variables may matter. As a robustness check, we consider the alternative ordering and we obtain that the findings are basically very similar. An Appendix with all these results is available from the authors upon request.

⁹Looking at the stochastic properties of the time series, the Augmented Dickey–Fuller test (whose null hypothesis is the existence of a unit root) indicates that we fail to reject the null hypothesis for the levels of the U.S. EER and the nominal oil price at the 5% significance level, with the p-values being 0.437 and 0.066 when the intercept and trend are considered (0.3441 and 0.1428 when the intercept is only included), respectively. However, we reject the null hypothesis when the first differences are considered, with the p-value being 0.000 for both variables. Given that both variables appear to be integrated of order 1, we test for cointegration by using the Johansen cointegration test. The results of this test indicates that we fail to reject the null hypothesis of no cointegration. In any case, authors such as

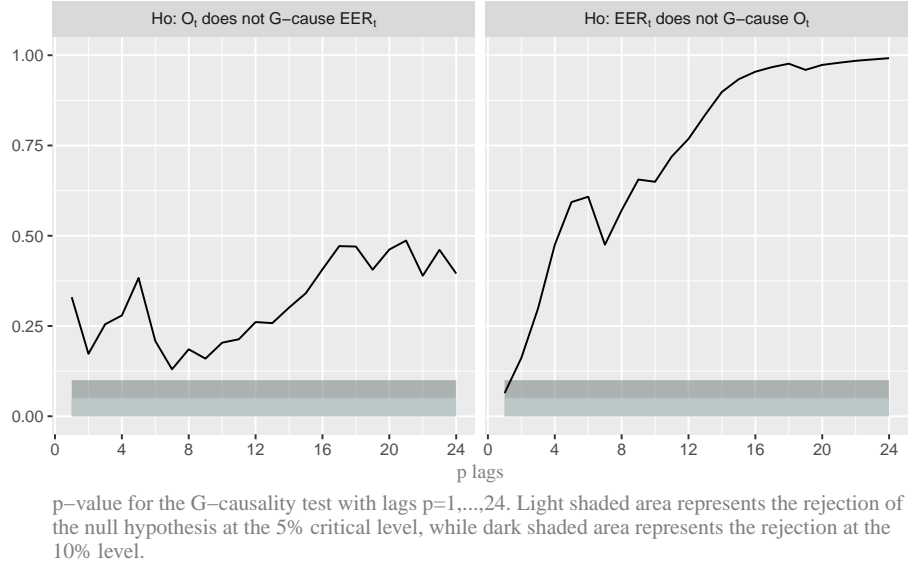


Figure 3: p -values for the linear Granger-causality test

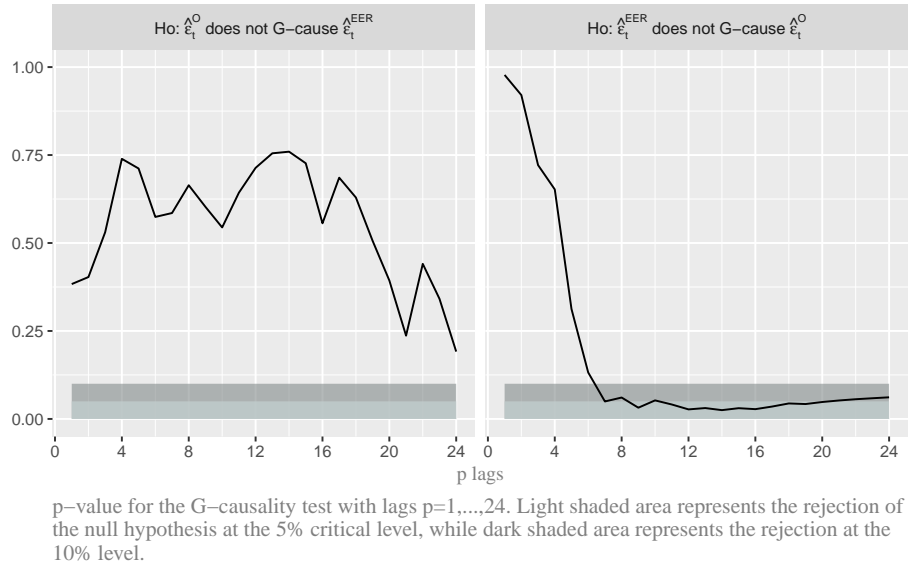


Figure 4: p -values for the nonlinear causality test

variance-covariance matrix Ψ .

We select two lags ($p = 2$) based on Schwarz Information Criterion. This choice is consistent with other studies of the related literature (see Fratzscher et al., 2014; Ferraro et al., 2015). To identify the bivariate VAR model, we consider the ordering in which exchange rate has a contemporaneous effect on oil price, but not the reverse. This ordering is based on the results of causality described in the previous Section. We calculate the impulse response of exchange rate to one standard deviation (s.d.) oil price shock, the impulse response of oil price to one s.d. exchange rate shock and their one standard deviation confidence bands obtained through bootstrap procedure with 10,000 draws.

3.2 TVP-VAR model

It seems clear that the relationship between nominal oil price and U.S. EER has changed over time (see Figures 1 and 2). Thus, we consider a time-varying parameter (TVP) model similar to the model implemented in Primiceri (2005) and Del Negro and Primiceri (2015). This model allows us to capture the effects of oil price (exchange rate) shocks over time by means of a flexible approach, with the VAR coefficients and variance-covariance matrix changing over time.

The following TVP-VAR model is considered:

$$y_t = a_t + \sum_{j=1}^p A_{j,t} y_{t-j} + \mu_t \quad (2)$$

where y_t is a (2×1) vector that contains exchange rate and oil price with $t = 1, \dots, T$; a_t is a (2×1) vector of time-varying (TV) coefficients; $A_{1,t}, \dots, A_{p,t}$ are (2×2) matrices of TV coefficients, and μ_t is a (2×1) vector of heteroskedastic unobservable shocks with (2×2) variance-covariance matrix Ω_t (specifically, $\mu_t \sim \mathcal{N}(0, \Omega_t)$).

This model can be rewritten as:

$$y_t = (I_2 \otimes X_t) \alpha_t + \mu_t$$

where I_2 is a 2-dimensional identity matrix; \otimes denotes the Kronecker product; $X_t = [1, y'_{t-1}, \dots, y'_{t-p}]$ is the vector of $1 \times (1 + 2p)$ explanatory variables, and $\alpha_t = \text{vec}(A_t)$ is the stacked vector of TV coefficients $A_t = (a_t \ A_{1,t} \dots A_{p,t})$.

Following Primiceri (2005), we consider the triangular reduction of the variance-covariance matrix Ω_t :

$$B_t \Omega_t B_t' = \Sigma_t \Sigma_t'$$

where B_t is the lower triangular matrix of error covariances with ones on the diagonal and Σ_t is the diagonal matrix with diagonal elements being the TV

Sims et al. (1990), Hamilton (1994) and Ramaswamy and Sløk (1998) state that it is possible to perform the study in levels allowing for implicit cointegrating relationships in the data if there are and still have consistent estimates of the parameters.

error deviations.¹⁰ Therefore, the TVP-VAR model is written as:

$$y_t = (I_2 \otimes X_t)\alpha_t + B_t^{-1}\Sigma_t\varepsilon_t,$$

with $\varepsilon_t \sim \mathcal{N}(0, \mathcal{I}_2)$.

The dynamics of the TV parameters is specified as:

$$\alpha_t = \alpha_{t-1} + \nu_t$$

$$b_t = b_{t-1} + \zeta_t$$

$$\log \sigma_t = \log \sigma_{t-1} + \eta_t$$

where α_t describes the dynamics of the coefficients, b_t describes the dynamics of the non-zero and non-one elements of matrix B_t and σ_t is the stochastic volatility model which describes the dynamics of the diagonal matrix Σ_t .

It is assumed that the error terms $(\varepsilon_t, \nu_t, \zeta_t, \eta_t)$ are jointly normally distributed with the variance covariance matrix (V) matrix being:

$$V = Var \left(\begin{bmatrix} \varepsilon_t \\ \nu_t \\ \zeta_t \\ \eta_t \end{bmatrix} \right) = \begin{bmatrix} I_2 & 0 & 0 & 0 \\ 0 & Q & 0 & 0 \\ 0 & 0 & S & 0 \\ 0 & 0 & 0 & W \end{bmatrix}$$

with Q, S and W being positive definite matrices.

The priors basically follow the same principles as in Primiceri (2005) and are summarized in Table 2. Unlike Primiceri (2005) who fixed $k_S = 0.1$, we have chosen $k_S = 1$ because this allows us to better capture the high volatility of both variables in the short-term.¹¹

These prior distributions are used to carry out Bayesian inference which involves Markov Chain Monte Carlo (MCMC) posterior simulation methods (Gibbs sampler) for the unobservable states α^T, B^T, Σ^T and the hyperparameters of the variance-covariance matrix V :

¹⁰This decomposition of the variance-covariance matrix mitigates the proliferation of parameters problems, which is important in this TVP-VAR. Although the order of the variables could matter given the lower matrix B_t , the results with TV covariances are very similar with different orders. In our case,

$$B_t = \begin{bmatrix} 1 & 0 \\ b_{21,t} & 1 \end{bmatrix} \quad \Sigma_t = \begin{bmatrix} \sigma_{1,t} & 0 \\ 0 & \sigma_{2,t} \end{bmatrix}$$

¹¹As Primiceri (2005) warns, posterior inference may be affected by the choice of k_Q, k_S and k_W . Thus, as a robustness check (available upon request), we also compute posterior inference using alternative values for k_Q, k_S and k_W . Specifically, following Primiceri (2005), we consider all possible combinations of $k_Q=0.01;0.05;0.1$, $k_S=0.01;0.1;1$ and $k_W=0.001;0.01$. The results are highly similar to those of our baseline specification.

Table 2: Prior distributions

Parameters		
	Prior family	Coefficients
α_0	$\mathcal{N}(\hat{\alpha}_{OLS}, k_\alpha \times \hat{V}(\hat{\alpha}_{OLS}))$	$k_\alpha=4$
B_0	$\mathcal{N}(\hat{B}_{OLS}, k_B \times \hat{V}(\hat{B}_{OLS}))$	$k_B=4$
$\log \sigma_0$	$\mathcal{N}(\log \hat{\sigma}_{OLS}, k_\sigma \times I_2)$	$k_\sigma=1$
Hyperparameters		
	Prior family	Coefficients
Q	$\mathcal{IW}(k_Q^2 \times pQ \times \hat{V}(\hat{\alpha}_{OLS}), pQ)$	$k_Q = 0.01$ $pQ=60$
S_1	$\mathcal{IW}(k_S^2 \times pS_1 \times \hat{V}(\hat{B}_{1,OLS}), pS_1)$	$k_S = 1$ $pS_1 = 2$
W	$\mathcal{IW}(k_W^2 \times pW \times I_2, pW)$	$k_W = 0.01$ $pW=3$

Note: \mathcal{N} and \mathcal{IW} denote the normal and independent inverse-Wishart distributions. $\hat{\alpha}_{OLS}, \hat{V}(\hat{\alpha}_{OLS}), \hat{B}_{OLS}, \hat{V}(\hat{B}_{OLS})$ and $\hat{\sigma}_{OLS}$ are OLS estimates of the VAR coefficients in a time-invariant VAR model for the training sample.

$$\begin{aligned}
& p(\alpha^T | y^T, B^T, \Sigma^T, V) \\
& p(B^T | y^T, \alpha^T, \Sigma^T, V) \\
& p(\Sigma^T | y^T, \alpha^T, B^T, V) \\
& p(V | y^T, \alpha^T, B^T, \Sigma^T)
\end{aligned}$$

The simulations are based on 50000 iterations for the Gibbs sampling and 5000 *burn-in* steps (initial training sample) to initialize the sample. The length of the training sample used for determining prior parameters via least squares is 60.

4 Results

4.1 VAR model

The impulse response functions from the (time-invariant) VAR model are depicted in Figure 5.¹² On the one hand, they show that an oil price shock leads to a depreciation of the U.S. EER within the first 7 months and an appreciation afterwards. On the other hand, the impact of a positive shock on U.S. EER tends to significantly reduce oil price. These findings show evidence in favor of a negative relationship between oil price and exchange rate, which is in concordance with most of the economic theory. Notwithstanding this, the positive

¹²We apply the Efron bootstrap percentile confidence interval with 2500 draws.

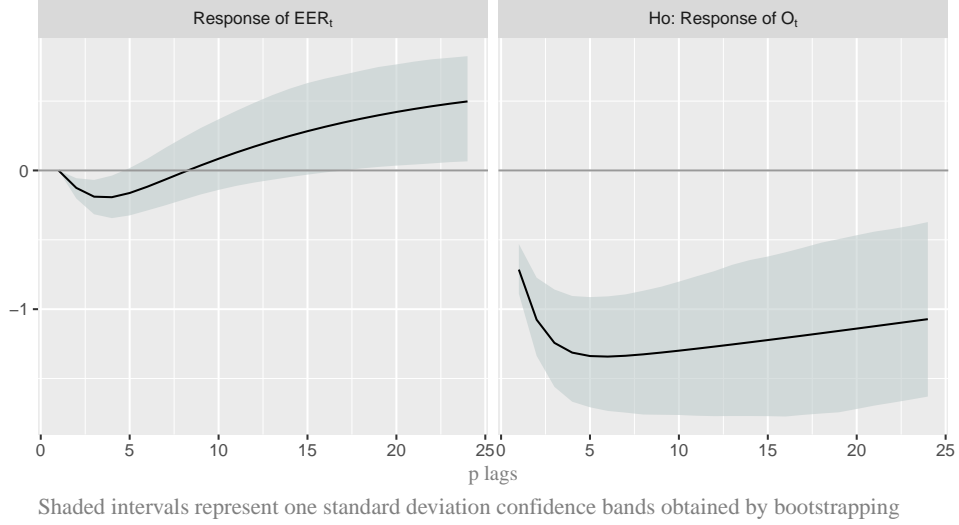


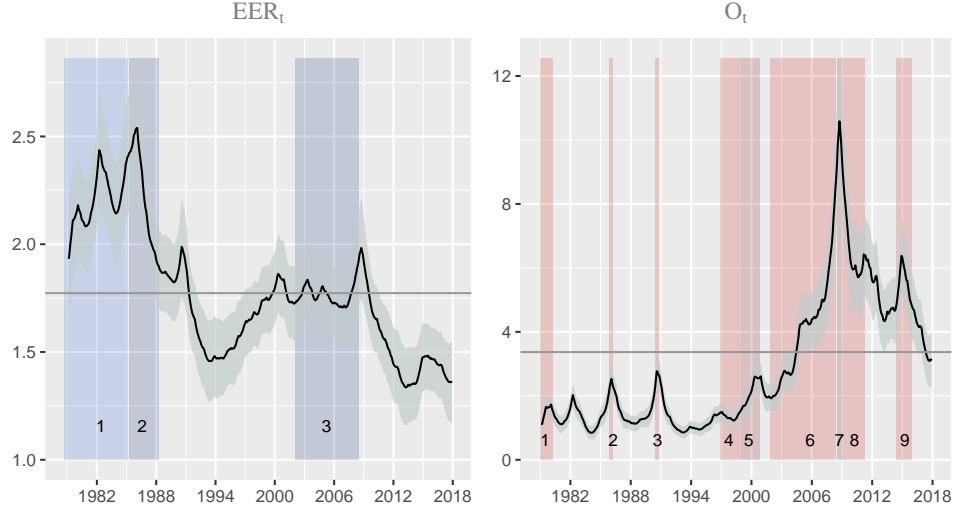
Figure 5: Response of one variable to one standard deviation shock of the other variable in the (time-invariant) VAR model for the whole period

response of U.S. EER to an oil shock found in the mid- and long-run can be explained by the petrodollar recycling argument.

4.2 TVP-VAR model

Unlike the (time-invariant) VAR model where the standard deviations of the error terms for U.S. EER and oil price are constant (1.773 and 3.368, respectively), the TVP-VAR model allows the standard deviations change over time, which has to be considered when we look at the impulse response to one standard deviation. Thus, Figure 6 shows the TV standard deviations obtained from the TVP-VAR model, which represent the shocks (unexpected movements) on U.S. EER and oil price that are originated by other turmoil in, for example, global or financial markets. The vertical shaded areas in Figure 6 correspond to the different shock episodes for U.S. EER and oil price depicted in Table 1. The Figure shows that exchange rate shocks were comparatively large before 1994 relative to the size of the shocks from that date onwards, while the opposite occurs with oil price shocks (which become increasingly high after 2000, with a peak in 2008). Interestingly, there is a striking coincidence between these U.S. EER and oil price shock episodes and the rise in the volatility of the corresponding errors. This finding reinforces the evidence showed in Figure 2, suggesting that the dynamic relationship between both variables has been strongly influenced by the volatility related with economic and political events.

Figure 7 presents the three-dimensional (3D) plot of time varying responses of one variable to one standard deviation of the other variable. This Figure



The horizontal gray line shows the standard deviations in the (time-invariant) VAR model. The black line displays the mean of the standard deviations while the grey area refers to one standard deviation confidence interval. Vertical shaded areas correspond to the episodes depicted in Table 1.

Figure 6: Standard deviations in the TVP-VAR model

shows heterogeneity in the response of U.S. EER to oil price shocks, with positive and negative values depending on the period of time in which the shock occurs. Also, the responses of oil price to exchange rate shocks are different over time, although they are all negative. However, the 3D plots are generally not easy to read and interpret. Moreover, they are responses to one standard deviation shocks, which correspond to a different-sized shock at point in time. Therefore, we re-scale the impulse response functions to one unit shock in order to compare the effects over time and we show the responses after 3 months, 12 months and 24 months for each period of time in which the shock happens (see Figure 8) in order to read and interpret more clearly.

Figure 8 shows that an increase in oil prices leads to a depreciation of U.S. EER in the short-run (responses after 3 months) during the whole sample period especially since 1990. These responses turn out positive (i.e., an appreciation appears) in the long-run for the whole period, with the exception of the period between 2002 and 2014, in which the depreciation remains. Moreover, the long-run responses seem to be stronger before the beginning of the 2000s than later on. Therefore, the results show evidence in favor of the heterogeneity in the response although there is a similar sign pattern over time: U.S. EER reacts negatively to oil price increases in the short-run (which is in line with most of economic theory) and positively in the long-run before the 2000s (which is consistent with the petrodollar recycling argument).

To analyze the extent to which the reactions of U.S. EER to oil price shocks

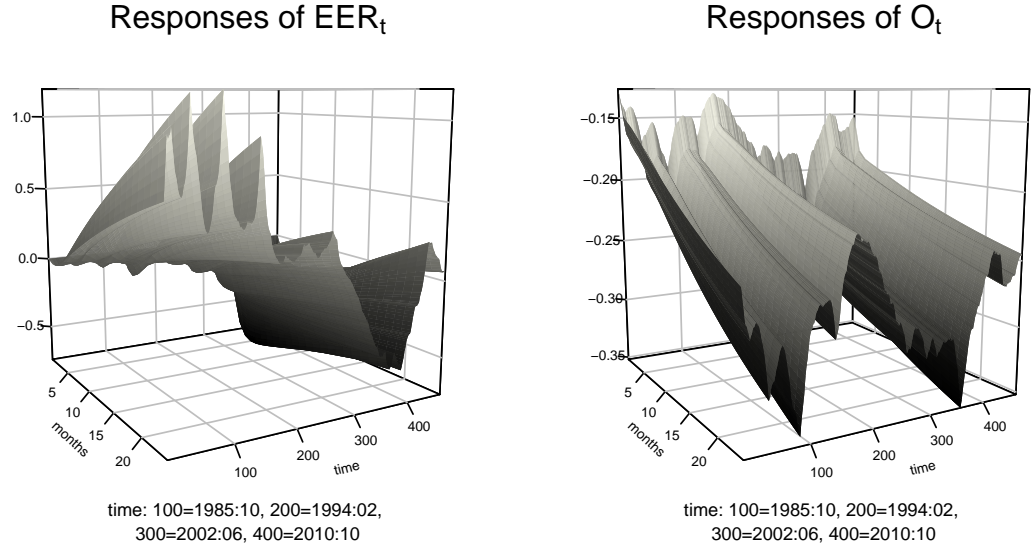


Figure 7: 3D plot of time-varying responses of one variable to one standard deviation shock of the other variable in the TVP-VAR model for the whole period

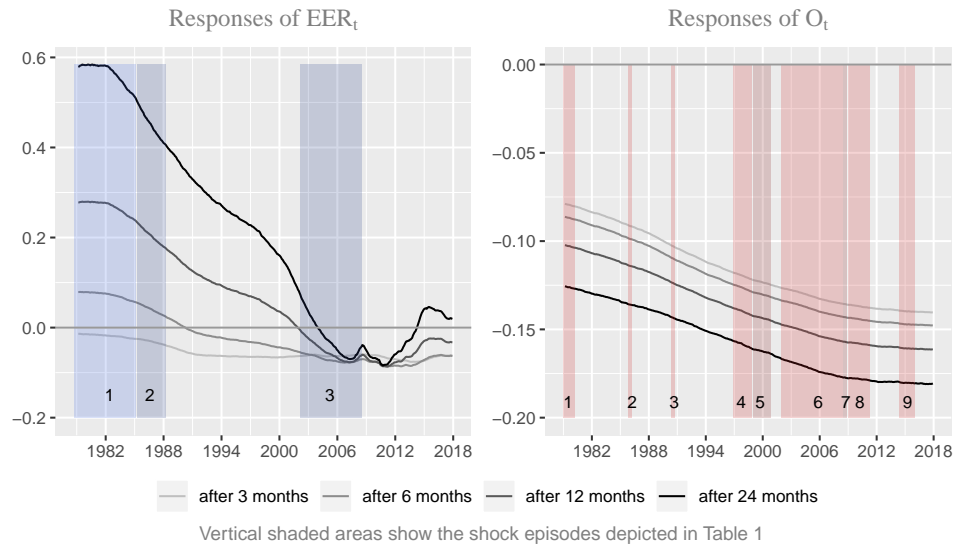


Figure 8: Responses of one variable to one unit shock of the other variable after 3, 6, 12 and 24 months (TVP-VAR model)

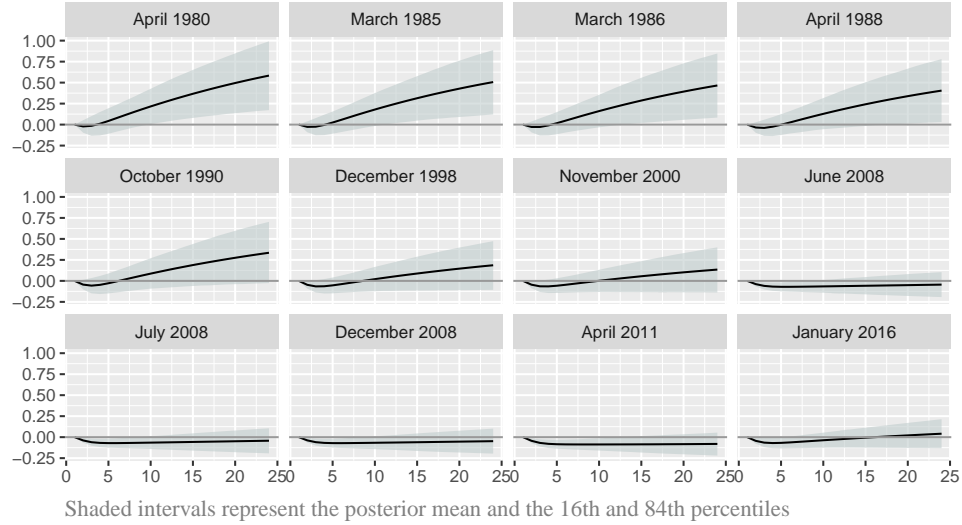


Figure 9: Response of U.S. EER to one unit oil price shock (TVP-VAR model) in the shock episodes

are similar across different shock episodes, Figure 9 presents the responses of U.S. EER to oil price shocks together with the 16th and 84th percentiles for the nine oil price shock episodes and the three exchange rate shock episodes depicted in Table 1.¹³ As was pointed out, the responses are negative in the short-run and turn out positive in the long-run in most episodes. However, the oil price movements have only had a significant statistically influence on exchange rate in the shock episodes occurred before the 1990s.

Figure 8 also presents the reaction of oil price to an appreciation of U.S. EER. The responses are negative in the short- and long-run, although the reactions are more intensive from the beginning of the 1990s onwards. The reactions differ across time periods, with the negative reaction being higher over time. These responses can be better appreciated when we look at the responses across different shock episodes (Figure 10). Thus, Figure 10 shows that the responses are negative and statistically significant for the nine oil price shock episodes and the three exchange rate shock episodes. Therefore, oil price declines after an appreciation of U.S. EER, which is in concordance with the economic theory.

¹³We only present the responses in the date that corresponds to the end of the shock episodes. The responses are broadly similar for any date we consider inside a specific shock episode.

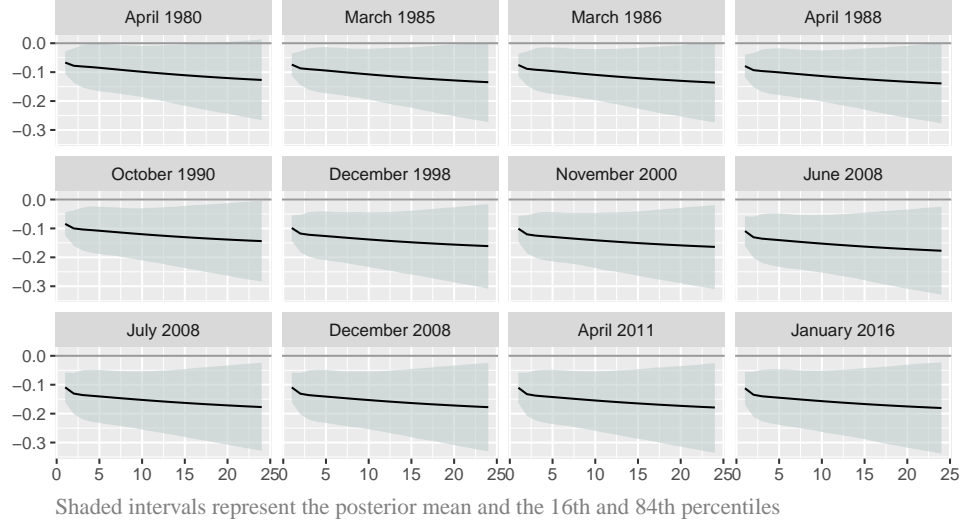


Figure 10: Responses of oil price to one unit U.S. EER shock (TVP-VAR model) in the shock episodes

5 Conclusions

Conventional wisdom holds that exchange rate is an important determinant of the trade balance, which is one of the key components of GDP, so that any movement in the exchange rate can have a relevant effect on the evolution of macroeconomic variables. Moreover, the USD exchange rate is especially relevant because USD is the standard currency of international trade. Besides, crude oil, which is considered to be a basic input to production, one of the main representatives of the large commodity markets and so one of the main indicators of economic activity worldwide, is priced in USD. Therefore, the evolution of the exchange rate and crude oil markets is closely related and there is no doubt about the interest of knowing the relationship between both markets for decision makers since their movements can influence key macroeconomic indicators.

This paper contributes to better understand the dynamic interaction between U.S. effective exchange rate (EER) and oil price by considering a Time-Varying Parameter VAR model with the use of monthly data from 1974 to 2017. Unlike the (time-invariant) VAR model which considers that the responses of one variable to the shock of the other are equal across different period of time, the TVP-VAR model allows that these responses change over time without establishing specific breaks.

The negative sign patterns of U.S. EER to oil price shocks in the short-run are highly similar across different period of time. This finding is consistent with most of economic theory, which establishes a depreciation after an increase in oil prices. The long-run responses of U.S. EER to oil price shocks differ qualitative

and quantitatively. These responses are positive before the mid-2000s, which is in line with the petrodollar recycling argument, but negative reactions appear afterwards.

The oil price declines after an appreciation of U.S. EER, which is in conformity with the economic theory.

Looking at the responses in the shock episodes, we observe the same pattern previously described. In particular, the reaction of U.S. EER to an oil price shock is negative in the short-run and positive in the long-run for most episodes, but it is only statistically significant for the shock episodes before the 1990s. The responses of oil price to an appreciation of U.S. EER are negative and statistically significant, being more intensive after the 1990s.

Therefore, these findings highlight the importance of considering the period of time in which the oil price shock occurs because the U.S. EER response may differ over time and, consequently, the economic policy reaction which is required to counteract such a shock may also differ. Moreover, the decline in oil price observed after an appreciation of U.S. EER is not the same over time and it may generate different adverse effects on investment depending on the period of time the appreciation takes place. The knowledge of such effects may help financial investors to diversify their investments in order to optimize the risk-return profile of their portfolios.

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