Time-varying relationship between oil price and exchange rate

César Castro*[1] and Rebeca Jiménez-Rodríguez†[2]

[1]Department of Economics, University of Salamanca, Spain.
[2]Department of Economics, IME, University of Salamanca, Spain.

March 28, 2018

Abstract

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. 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 different period of time, 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, with the response being similar in the short-run but different in the long-run for each period of 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

*E-mail: ccastrorozo@gmail.com
†Corresponding author. E-mail: rebeca.jimenez@usal.es

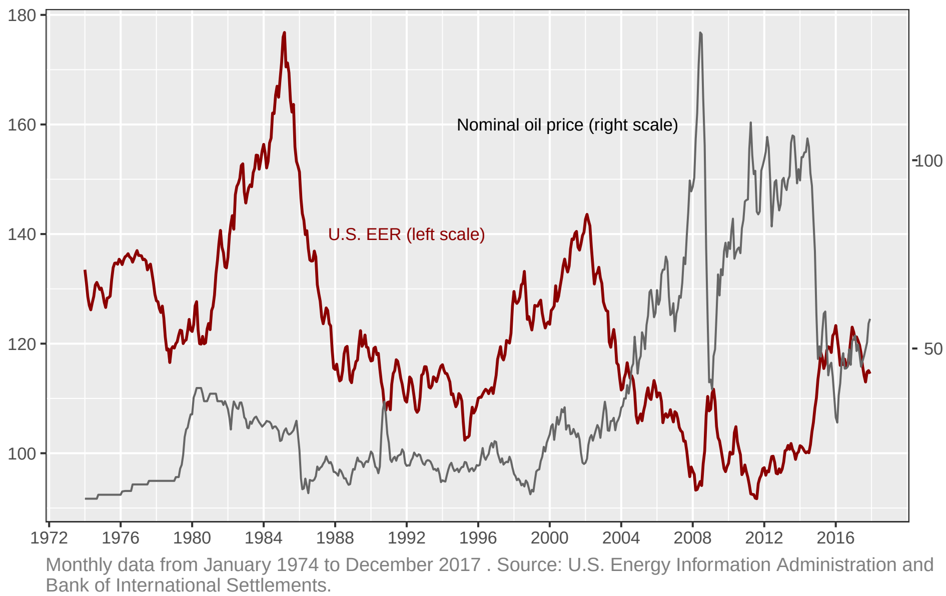


Figure 1: Nominal oil price and U.S. EER

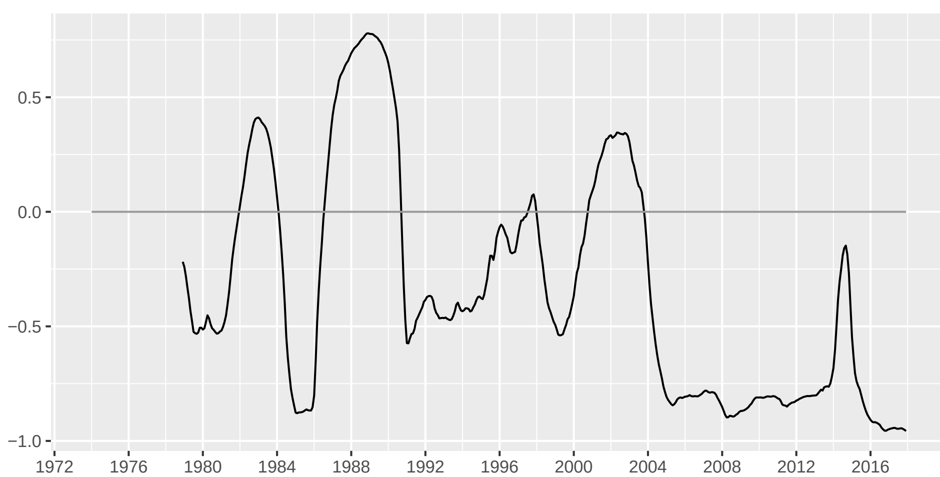


Figure 2: Five-year rolling correlation between nominal oil price and U.S. EER

the positive values predominate with the average correlation being 0.023. This 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 Iraq 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 world oil demand, OPEC oil production cutbacks and other factors such as weather and low levels of oil stock. 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 the 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

[1] Wang 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 afterwards.

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 the real oil price and the 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 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 export prices in relation to import prices in oil-exporting countries, which causes a positive impact on the terms of trade (which may eventually give rise to a Dutch Disease phenomenon) and the appreciation 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

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

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

[4]Chen 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.

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. Furthermore, although the supply-side effects are less discussed in the literature because they depend on several other factors which affect price setting and production, the main idea is that a depreciation of USD declines oil supply in oil-exporting countries, which gives rise to an increase in oil prices.

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

This paper contributes to better understand the dynamic interaction between U.S. exchange rate and oil price. In doing so, we consider a Time-Varying Parameter (TVP) VAR model and we use monthly data from January 1974 to December 2017. We postulate that the negative and occasional positive relationship observed before the early 2000s was led by oil price shocks, but the sharp negative link found afterwards has been driven by exchange rate movements.

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 eight oil price shock episodes, of which 5 are positive, 2 are negative and 1 shows a swing movement negative-positive (see Table 1). Seven out of eight shocks are originated by global or oil-specific demand shocks and the last one for supply shock. 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 four shock episodes related to exchange rate movements.

	Start date	End date	Months	Total growth (%)	Event	Type of shock
				Oil shocks		
1	Jan-79	Apr-80	16	98	Iran revolution	Spec.-Demand
2	Nov-85	Mar-86	5	-89	OPEC collapse	Spec.-Demand
3	Jun-90	Oct-90	5	76	Kuwait war	Spec.-Demand
4	Dec-96	Dec-98	25	-81	Asian crisis	Spec.-Demand
	Feb-99	Nov-00	22	105		
5	Dec-01	Jun-08	62	194	Asian boom	Global Demand
6	Jul-08	Dec-08	6	-118	Great crisis	Demand
7	Feb-09	Apr-11	27	103	Global recover	Global Demand
8	Jun-14	Jan-16	21	-125	Weak growth	Supply
				Exchange rate shocks		
1	Jan-81	Mar-85	51	37		
2	Nov-96	Feb-02	64	26		
3	Feb-02	Jul-08	78	-42		
4	Jul-14	Mar-15	9	17		

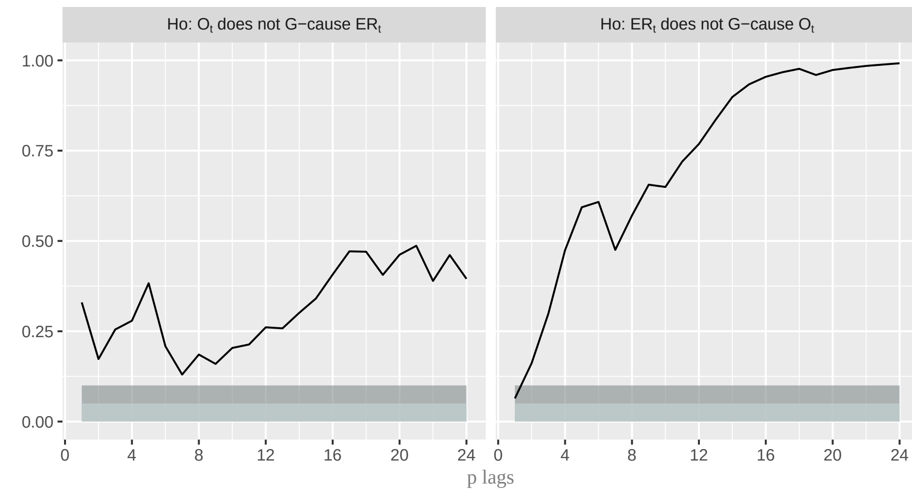
Table 1: Timing and duration of shock episodes

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 (ER_t). The right panel of Figure 3 shows that the null hypothesis that exchange rate does not G-cause oil price is only

[5] It is worth noting that the narrow effective exchange rate comprises 26 economies, with weighting matrix for each period of time given at web page http://www.bis.org.

[6] Although 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.

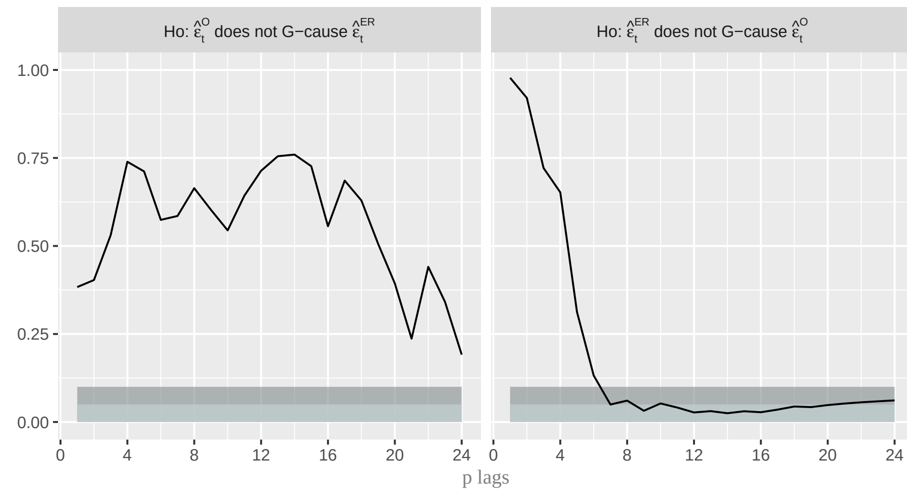


p−value for the G−causality test with lags p=1,...,24. Light shaded area represents the rejection of the null hypothesis at the 5% critical level, while dark shaded area represents the rejection at the 10% level.

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

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 $\hat{\varepsilon}_t^{ER}$, 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 $[ER_t, O_t]$ when we apply VAR models.[7]

[7] We 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.



p−value for the G−causality test with lags p=1,...,24. Light shaded area represents the rejection of the null hypothesis at the 5% critical level, while dark shaded area represents the rejection at the 10% level.

Figure 4: p-values for the nonlinear causality test

3 Methodology

3.1 VAR model

We analyze the relationship between oil prices and exchange rates 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

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

with y_t being a (2×1) vector that contains the U.S. EER and the nominal oil price,[8] and with ε_t being a generalization of a white noise process with variance-covariance matrix Ω. 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

[8] In this paper, we do not carry out an explicit study of the long-run relationship. By performing the study in levels we allow for implicit cointegrating relationships in the data if there are, and still have consistent estimates of the parameters (see, e.g., Sims et al., 1990; Hamilton, 1994 and Ramaswamy and Sløk, 1998.)

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:

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

where y_t is a (2×1) vector that contains oil price and exchange rate with $t = 1, \ldots, T$; a_t is a (2×1) vector of time-varying (TV) coefficients; $A_{1,t}, \ldots, A_{p,t}$ 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; $X_t = [1, y'_{t-1}, \ldots y'_{t-p}]$ is the vector of $1 \times (1 + 2p)$ explanatory variables, and $\alpha = vec(A_t)$ is the stacked vector of TV coefficients $A_t = (a_t\ A_{1,t} \ldots A_{p,t})$.

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 error deviations.[9] Thus, ε_t will have a diagonal covariance matrix $\Sigma_t\Sigma'_t$ (specifically, $\varepsilon_t \sim \mathcal{N}(0, \Sigma_t\Sigma'_t)$. Therefore, the TVP-VAR model is written as:

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

[9] This decomposition of the variance 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,

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

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 follow the same principles as in Primiceri (2005) and are summarized in Table 2.

Table 2: Prior distributions

	Parameters	
	Prior family	Coefficients
α_0	$\mathcal{N}(\hat{\alpha}_{OLS}\ ,\ k_\alpha \times \hat{V}(\hat{\alpha}_{OLS}))$	k_α=4
B_0	$\mathcal{N}(\hat{B}_{OLS}\ ,\ k_B \times \hat{V}(\hat{B}_{OLS}))$	k_B=4
log σ_0	$\mathcal{N}(\log\hat{\sigma}_{OLS}\ ,\ k_\sigma \times I_2)$	k_σ=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=84
S_1	$\mathcal{IW}(k_S^2 \times pS_1 \times \hat{V}(\hat{B}_{1,OLS})\ ,\ pS_1)$	$k_S = 0.1$ 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. $\hat{\alpha}_{OLS}, \hat{V}(\hat{\alpha}_{OLS}), \hat{B}_{OLS}, \hat{V}(\hat{B}_{OLS})$ are OLS estimates of the VAR coefficients in a time-invariant VAR model for the training sample.

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:

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

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 84.

4 Results

4.1 VAR model

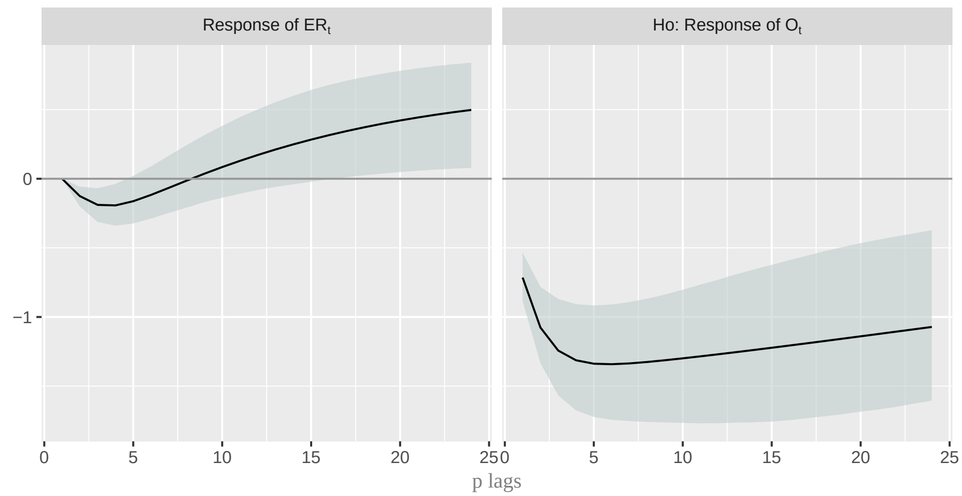
The impulse response functions from the (time-invariant) VAR model are depicted in Figure 5. On the one hand, they show that an oil price shock leads to a depreciation of the U.S. EER within the first 7 months and an appreciation afterwards. On the other hand, the impact of a positive shock on U.S. EER 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 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 deviation of the errors for U.S. EER and oil price is 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 oil price and U.S. EER 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 depicted in Table 1.[10] This Figure also 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).

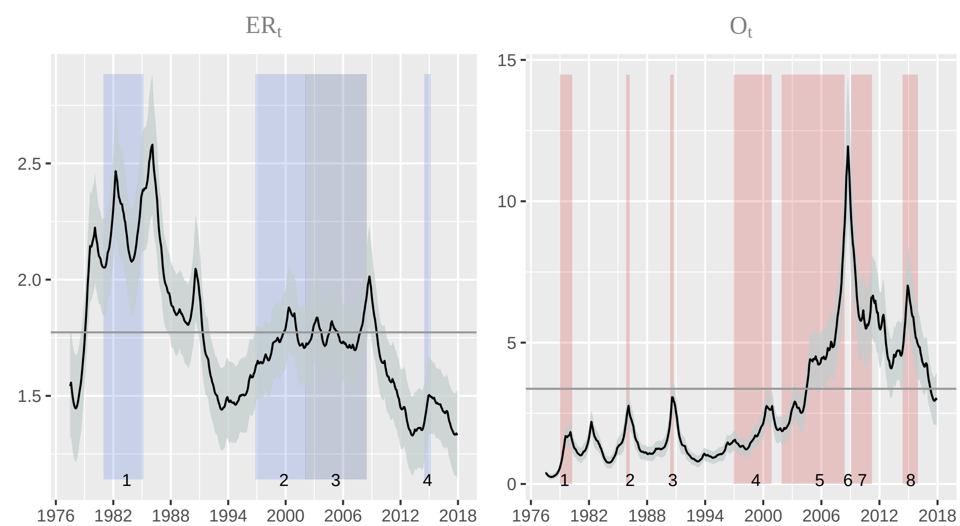
Figure 7 presents the three-dimensional (3D) plot of time varying responses of one variable to one standard deviation of the other variable. This Figure

[10]It is worth noting that there seems to be a striking coincidence between the unexpected oil price shocks and the rise in the volatility of the errors for U.S. EER and especially for oil price.



Shaded intervals represent one standard deviation confidence bands obtained by bootstrapping

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



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

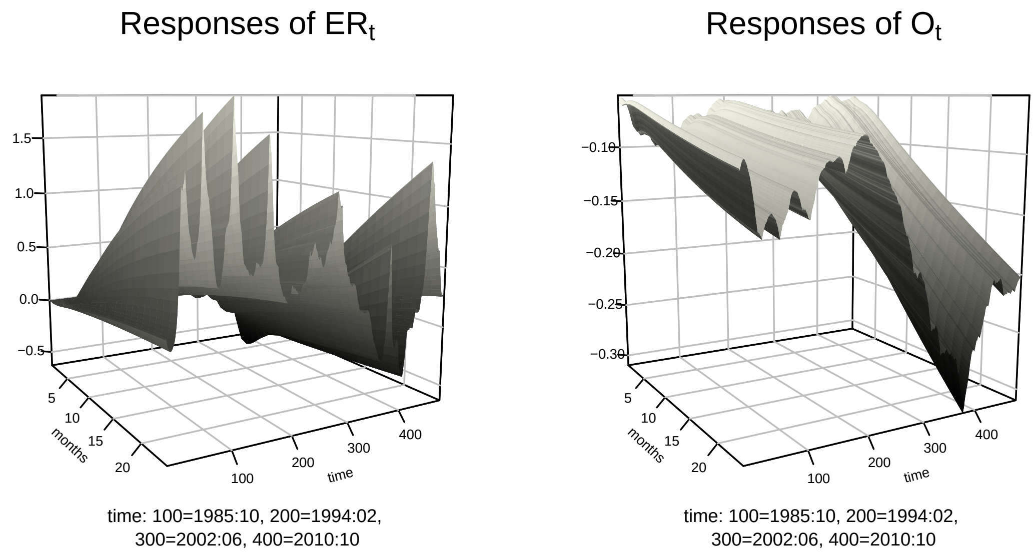


Figure 7: 3D plot of time-varying responses of one variable to one standard deviation shock of the other variable in the TVP-VAR model for the whole period

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, 6 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. These responses turn out positive (i.e., an appreciation appears) in the mid- and 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 mid- and 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

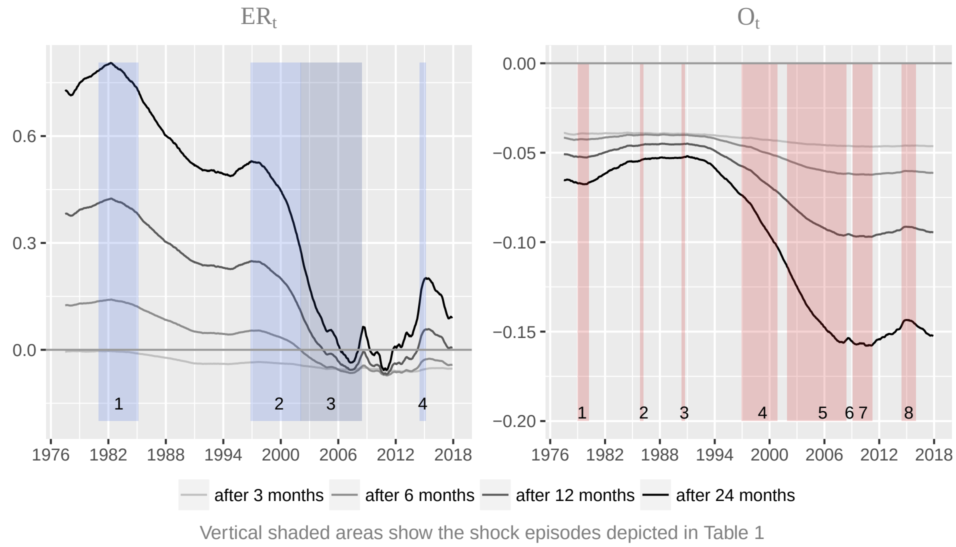


Figure 8: Responses of one variable to one unit shock of the other variable after 3, 6, 12 and 24 months (TVP-VAR model)

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 eight oil price shock episodes and the four exchange rate shock episodes.[11] As was pointed out, the responses are negative in the short-run and turn out positive in the mid- and 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 2000s.

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 long-run reactions are more intensive from the beginning of the 1990s on. The reactions are relatively similar in the short-run but they differ in the long-run across time periods, with the highest negative impact occurring during the global financial crisis. 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 for the eight oil price shock episodes and the four exchange rate shock episodes, although they are only statistically significant at very short-run. Therefore, oil price declines after an appreciation of U.S. EER, which is in concordance with the economic theory.

[11] We 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 an specific shock episode.

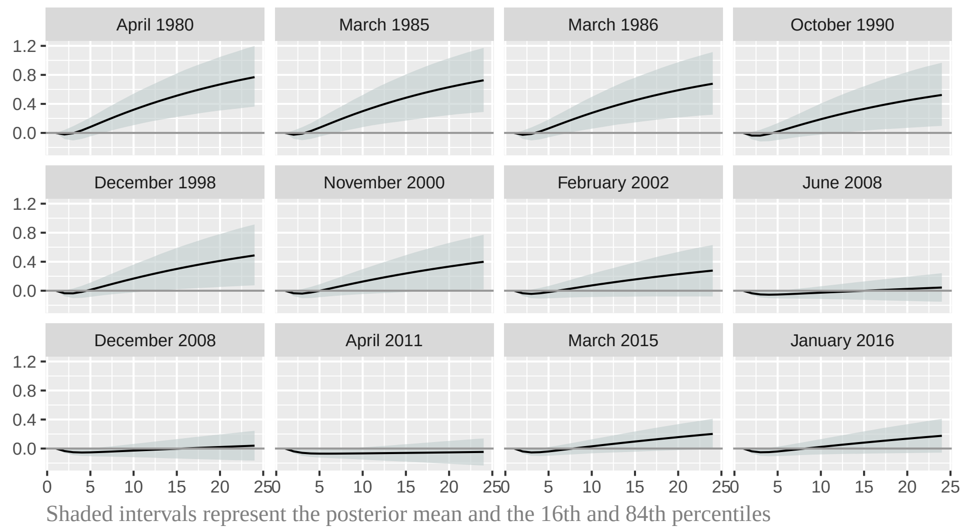


Figure 9: Response of U.S. EER to one unit oil price shock (TVP-VAR model) in the shock episodes

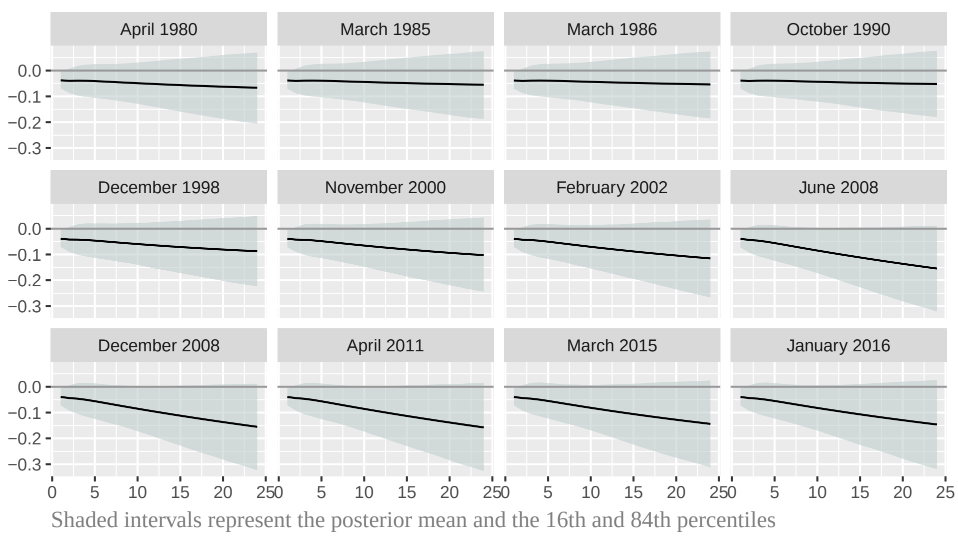


Figure 10: Responses of oil price to one unit U.S. EER shock (TVP-VAR model) in the shock episodes

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 US dollar (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 mid- and long-run responses of U.S. EER to oil price shocks differ qualitative and quantitatively. These responses are positive before the mid-2000s, which 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. While the negative short-run reaction has been similar across different period of time, the long-run reaction differs. In fact, the pattern responses have been highly similar before the mid-1990s, date from which the responses start to be more intensive, with the highest impact being observed in the global financial crisis.

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 2000s. The responses of oil price to an appreciation of U.S. EER are negative in the short- and long-run, although they only have a statistically significant at very short-run.

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 to 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.

Acknowledgements

Rebeca Jiménez-Rodríguez acknowledges support from the Research Grant SA072U16 (Junta de Castilla y León).

References

Akram, F. (2009). Commodity prices, interest rates and the dollar. *Energy Economics*, 31(6):838–851.

Amano, R. and Van Norden, S. (1998). Exchange rates and oil prices. *Review of International Economics*, 6(4):683–694.

Backus, D. K. and Crucini, M. J. (2000). Oil prices and the terms of trade. *Review of International Economics*, 50:185–213.

Bampinas, G. and Panagiotidis, T. (2015). On the relationship between oil and gold before and after financial crisis: linear, nonlinear and time-varying causality testing. *Studies in Nonlinear Dynamics and Econometrics*, 19(5):657–668.

Beckmann, J. and Czudaj, R. (2013). Is there a homogeneous causality pattern between oil prices and currencies of oil importers and exporters? *Energy Economics*, 40:665–678.

Blanchard, O. and Galí, J. (2010). The macroeconomic effects of oil shock: Why are the 2000s so different from the 1970s? In Galí, J. and Gertler, M., editors, *International Dimensions of Monetary Policy*, pages 373–421. University of Chicago Press, Chicago, IL.

Blomberg, S. and Harris, E. (1995). The commodity-consumer price connection: Fact or fable? *Economic Policy Review*, 1(3):21–38.

Bodenstein, M., Erceg, C. J., and Guerrieri, L. (2011). Oil shocks and external adjustment. *Journal of International Economics*, 83(2):168–184.

Breitenfellner, A. and Cuaresma, J. C. (2008). Crude oil prices and the USD/EUR exchange rate. *Monetary Policy & the Economy*, pages 102–121.

Cashin, P., Cespedes, L. F., and Sahay, R. (2004). Commodity currencies and the real exchange rate. *Journal of Development Economics*, 75:239–268.

Chen, S.-S. and Chen, H. (2007). Oil prices and real exchange rates. *Energy Economics*, 29(3):390–404.

Chen, Y.-c. and Rogoff, K. (2003). Commodity currencies. *Journal of International Economics*, 60(1):133–160.

Chen, Y.-c., Rogoff, K. S., and Rossi, B. (2010). Can exchange rates forecast commodity prices? *The Quarterly Journal of Economics*, 125(3):1145–1194.

Coudert, V. and Mignon, V. (2016). Reassessing the empirical relationship between the oil price and the dollar. *Energy Policy*, 95:147–157.

DeGregorio, J., Landerretche, O., Neilson, C., Broda, C., and Rigobon, R. (2007). Another pass-through bites the dust? Oil prices and inflation. *Economia*, 7(2):155–208.

Del Negro, M. and Primiceri, G. E. (2015). Time-varying structural vector autoregressions and monetary policy: A corrigendum. *The Review of Economic Studies*, 82(4):1342–1345.

Diks, C. and Panchenko, V. (2006). A new statistic and practical guidelines for nonparametric granger causality testing. *Journal of Economic Dynamics and Control*, 30:1647–1669.

Ferraro, D., Rogoff, K., and Rossi, B. (2015). Can oil prices forecast exchange rates? an empirical analysis of the relationship between commodity prices and exchange rates. *Journal of International Money and Finance*, 54:116–141.

Fratzscher, M., Schneider, D., and Robays, I. V. (2014). Oil prices, exchange rates and asset prices. *ECB Working Paper Series*, (1689).

Golub, S. S. (1983). Oil prices and exchange rates. *The Economic Journal*, 93(371):576–593.

Habib, M. M., Butzer, S., and Stracca, L. (2016). Global exchange rate configurations: Do oil shocks matter? *IMF Economic Review*, 64(3):443–470.

Hamilton, J. (1994). *Time Series Analysis*. Princeton University Press.

Hiemstra, C. and Jones, J. D. (1994). Testing for linear and nonlinear granger causality in the stock price-volume relation. *The Journal of Finance*, 49(5):1639–1664.

Krugman, P. (1983). Oil and the dollar. In Bhandari, J. S. and Putnam, B. H., editors, *Economic interdependence and flexible exchange rates*. MIT Press, Cambridge.

Lizardo, R. A. and Mollick, A. V. (2010). Oil price fluctuations and U.S. dollar exchange rates. *Energy Economics*, 32(2):399–408.

Primiceri, G. E. (2005). Time varying structural vector autoregressions and monetary policy. *The Review of Economic Studies*, 72(3):821–852.

Ramaswamy, R. and Sløk, T. (1998). The real effects of monetary policy in the european union: What are the differences? *Staff Papers (International Monetary Fund)*, 45(2):374–396.

Sims, C. A., Stock, J. H., and Watson, M. W. (1990). Inference in linear time series models with some unit roots. *Econometrica*, 58(1):113–144.

Trehan, B. (1986). Oil prices, exchange rates and the U.S. economy: An empirical investigation. *Economic Review*, 4:25–43.

Wang, Y. and Wu, C. (2012). Energy prices and exchange rates of the u.s. dollar: Further evidence from linear and nonlinear causality analysis. *Economic Modelling*, 29(6):2289–2297.

Yousefi, A. and Wirjanto, T. S. (2004). The empirical role of the exchange rate on the crude-oil price formation. *Energy Economics*, 26(5):783–799.

Zhang, Y. J., Fan, Y., Tsai, H. T., and Wei, Y. M. (2008). Spillover effect of us dollar exchange rate on oil prices. *Journal of Policy Modeling*, 30(6):973–991.