Time-varying relationship between oil price changes and exchange rates

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June 14, 2017

Draft version: Please do not quote or cite without permission from the authors.

Abstract

This paper contributes to better understand the dynamic interaction between exchange rates and oil prices for the euro area. In doing so, we consider a Time-Varying Parameter VAR model with the use of daily data from 1987 to 2017. Over this period, the euro area has experienced major changes in oil market conditions, including a high role of global demand and its linkage with financial markets. We postulate the weak negative relationship observed before the early 2000s was led by exchange rate shocks, but the sharp link found later was due to oil price shocks. We analyze the potential differences of the effects of oil price shocks on exchange rates with a particular focus on the different origin of the oil price shock (supply, global or specific demand) and the role of financial markets after the early 2000s and the likely appearance of structural breaks.

Keywords. Oil price, Exchange rates, Euro area.

1 Introduction

It is observed a negative relationship between the price of Brent crude oil (expressed in U.S. dollars) and the bilateral exchange rates euro/U.S. dollar (€/USD) from the early 2000s onwards (see Figure 1). From a theoretical standpoint, authors such as Golub (1983) and Krugman (1983) highlighted that after

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Figure 1: One-year rolling correlation between the log-differences of nominal oil price (in USD) and nominal exchange rate (€/USD) using daily data from 22 May 1987 to 13 January 2017.

an increase in oil prices a depreciation of the domestic currency is expected in oil-importing economies and an appreciation is expected in oil-exporting economies. Blomberg and Harris (1995) also show the mechanism through which exchange rate changes can affect oil prices on the basis of the law of one price for tradable goods. The latter means that, given that crude oil is an international commodity traded in USD, if the USD weakens with respect to other currencies the price of crude oil for these countries is reduced (since their purchasing power is increased) and, consequently, their oil demand increases, which leads to higher crude oil prices.

The empirical literature has analysed the direction of the causality existing between oil prices and exchange rates. Whereas there are studies that emphasize the role of the exchange rates anticipating the movements in oil prices (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 focus on the reverse anticipation, i.e., oil price changes anticipate the changes in exchange rates (see, e.g., Amano and Van Norden, 1998; Chen and Chen, 2007; Lizardo and Mollick, 2010; Ferraro et al., 2015; Habib et al., 2016). There are also researchers that consider the causality in both directions (see, e.g., Wang and Wu, 2012; Fratzscher et al., 2014).

1Wang and Wu (2012) find that a unidirectional causality relationship from petroleum prices to exchange rates in the period before great crisis, and a bidirectional afterward.
The differences related to the direction of the causality can be related, among others, to three key issues. First, the frequency of the data. For example, in a study for some small exporting countries, Ferraro et al. (2015) argue that commodity prices (including oil prices) contain significant valuable information for predicting exchange rates at daily data, while the predictive content is weaker at monthly and quarterly frequency. Second, the oil-dependence of the country (i.e., being either an oil-importing or an oil-exporting country) for each specific period of time. Thus, Ferraro et al. (2015), for instance, point out the improvement in the prediction of exchange rate by means of a forecast model including oil prices after Canada became a net oil-exporting country. Third, the 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. The latter two issues may have to do with the possible existence of structural breaks, but there is not a clear conclusion about them in the related literature. For example, Chen and Chen (2007) do not find evidence of structural breaks for G-7 countries in the relationship between oil prices and real exchange rates by using monthly data from January 1972 to October 2005. However, applying the Chow-type-heteroskedasticity-robust wald-statistic for parameter instability to Granger causality regressions, Chen et al. (2010), in quarterly data, and Fratzscher et al. (2014), in U.S. daily data, show evidence of structural breaks in the early 2000s.

Another important issue on the relationship between oil prices and exchange rates is the origin and transmission of their respective shocks. On the one hand, the main sources of exchange rate shocks are real shocks, such as oil price, demand, fiscal policy and productivity shocks (see, e.g., Clarida and Gali, 1994; Juvenal, 2011). Thus, the devaluation of the USD may increase world oil prices at least for three main reasons: i) rising oil demand in oil-importing countries (in local currency); ii) decreasing the supply in oil-exporting countries; and iii) lowering the return on the USD denominated financial assets, increasing the attractiveness of oil and other commodities as alternative assets (portfolio rebalancing argument). On the other hand, the origin of oil price shocks can be related to the oil market shocks (i.e., supply, global or oil-specific demand shocks, see Kilian [2009]) and, more recently, with shocks in the exchange rate and financial markets (see Fratzscher et al. [2014]). Consequently, an oil-
importing region like the euro area needs to obtain USD by selling euros in order to buy crude oil, and those euros may be used by oil-exporting regions to buy goods and services produced in the euro area. Therefore, the level of interaction between regions causes the deterioration of the trade balance and the current account, which is solved through movements in exchange rates. Hence, higher oil price decreases the demand for dollars and thereby induce the devaluation of the USD as a consequence of the lower demand of oil in oil-importing countries and the larger interest in the oil as an alternative asset in relation with the USD.

This paper contributes to better understand the dynamic interaction between exchange rates and oil prices for the euro area. In doing so, we consider a Time-Varying Parameter VAR model with the use of daily data from 1987 to 2017. Over this period, the euro area has experienced major changes in oil market conditions, including a high role of global demand and its linkage with financial markets. We postulate the weak negative relationship observed before the early 2000s was led by exchange rate shocks, but the sharp link found later was due to oil price shocks. We analyze the potential differences of the effects of oil price shocks on exchange rates with a particular focus on the different origin of the oil price shock (supply, global or specific demand) and the role of financial markets after the early 2000s and the likely appearance of structural breaks.

2 Data

We consider the nominal Brent price in USD per barrel, which is provided by U.S. Energy Information Administration (EIA) web page (http://www.eia.gov) and the exchange rate €/USD, which is published by the Federal Reserve (http://www.federalreserve.gov). We have opted for daily data given that financial market exerts an important role in oil price changes.

The sample period runs from 22 May, 1987 to 31 May, 2017, with a total number of 7434 observations. Following Blanchard and Galí (2010), we define an oil price shock as a period in which the cumulative change in the log Brent price is above 50 percent and is sustained for more than 60 days. Thus we can distinguish 4 positive and 3 negative oil price shocks (see Table 1). Most of the oil price shocks are originated by global demand shocks, with three exceptions: oil-specific demand shock #1, global demand–financial shock #4 and global demand–supply shock #7. Moreover, most of the shocks have occurred in the process of oil market lead to an increase in oil prices, whereas high risk and risk aversion reduce oil price.

Despite the decline in oil consumption, the European dependence on oil imports has grown from 76% in 2000 to over 88% in 2014.

Cashin et al. (2004) have established the adjustment of real exchange rate in order to restore the long-run equilibrium relationship between the real exchange rates and real commodity prices for about one-third of 58 commodity-exporting countries.

Figure 2 displays the level of the nominal Brent price and the exchange rate €/USD, with the shadow areas depicting the oil price shocks reported in Table 1.
Figure 2: Exchange rates €/USD (left scale) and USD per barrel Brent price (right scale).

The shaded areas show the oil price shocks, according to the order in Table 1.

Although the Pearson correlation coefficient between the first-order differences of the logarithm of the series for the full sample is weak (-0.08), shocks #4 and #7 may suggest the existence of two structural breaks in data around 2002 and 2014 (see Figure 1 and Table 2). The first sub-period (characterized by a low correlation coefficient, 0.06), corresponds to a relative stable period of low Brent prices before 2002, disrupted by the first Gulf War in 1990 (shock #1)
and the Asian crisis in 1997 (shock #2). The second sub-period (2002-2014) shows the highest correlation coefficient (-0.29), and is associated with the upward trend between 2003 and 2008 caused by global demand in Asia (shock #4), although with the remarkable role of oil and other raw commodities as financial assets. Finally, the third period (after 2014) presents a low correlation (-0.04) similar to the correlation before 2002, and is related with the shock #7 and the considerable role of the global supply as the origin of the shock #7.

<table>
<thead>
<tr>
<th></th>
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</tr>
</thead>
<tbody>
<tr>
<td>Pearson</td>
<td>-0.08</td>
<td>0.06</td>
<td>-0.29</td>
<td>-0.04</td>
</tr>
<tr>
<td>Kendall</td>
<td>-0.05</td>
<td>0.02</td>
<td>-0.16</td>
<td>-0.02</td>
</tr>
<tr>
<td>Spearman</td>
<td>-0.08</td>
<td>0.04</td>
<td>-0.24</td>
<td>-0.03</td>
</tr>
</tbody>
</table>

Table 2: Correlation between Brent price per barrel in euros and exchange rates €/USD.

3 Model

Our modeling strategy is based on a time-varying Bayesian VAR framework (TVP-VAR), 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 shocks over time by means of a flexible approach, which allows the VAR coefficients and variance-covariance matrix change over time.

The following TVP-VAR model is considered:

\[ y_t = c_t + B_{1,t}y_{t-1} + \cdots + B_{2,t}y_{t-k} + u_t \quad t = 1, \ldots, 7341 \]  

(1)

where \( y_t \) is a \((2 \times 1)\) vector of observed endogenous variables; \( c_t \) is a \((2 \times 1)\) vector of time-varying (TV) coefficients that multiply constant term; and \( B_{1,t}, \ldots, B_{k,t} \) are matrices \((2 \times 2)\) of TV coefficients with \( k \) lags. This model can be rewritten as

\[ y_t = X_t' B_t + A_t^{-1} \Sigma_t \xi_t \]  

(2)

- \( \xi_t \) is the usual additive shock
- \( B_t = (c_t, B_{1,t}, B_{2,t}) \) represents all the TV coefficients of the model; \( X_t' = I_n \otimes [1, y_{t-1}', y_{t-2}'] \); \( I_n \) is a 2-dimensional identity matrix
- \( A_t \) is the lower triangular matrix \((2 \times 2)\) with TV simultaneous relations \( \alpha \) which represent the effects of innovation in one variable on the other
- \( \Sigma_t \) is the diagonal matrix \((2 \times 2)\) with TV standard deviations \( \sigma_t \)

The dynamics of the TV parameters, letting \( \alpha_t \) and \( \sigma_t \) vectors, is specified as follows:

\[ B_t = B_{t-1} + \nu_t \]  

(3)
\[ \alpha_t = \alpha_{t-1} + \zeta_t \] (4)

\[ \log \sigma_t = \log \sigma_{t-1} + \eta_t \] (5)

All the innovations in the model are assumed to be jointly normally distributed with the following assumptions on the variance covariance matrix (VCV):

\[
\begin{bmatrix}
   \varepsilon_t \\
   \nu_t \\
   \zeta_t \\
   \eta_t
\end{bmatrix} 
\sim \mathcal{N}
\begin{bmatrix}
   I_n & 0 & 0 & 0 \\
   0 & Q & 0 & 0 \\
   0 & 0 & S & 0 \\
   0 & 0 & 0 & W
\end{bmatrix}
\]

\( Q, S \) and \( W \) are positive definite matrices.

The priors follow the same principles as in Primiceri (2005) and are summarized in Table 3.

**Table 3: Prior distributions**

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Initial states</th>
<th>Prior family</th>
<th>Coefficients</th>
</tr>
</thead>
<tbody>
<tr>
<td>( B_0 )</td>
<td>TV coefficients</td>
<td>( \mathcal{N}(B_{OLS}, k_B \times V(B_{OLS})) )</td>
<td>( k_B = 4 )</td>
</tr>
<tr>
<td>( A_0 )</td>
<td>Simultaneous relations</td>
<td>( \mathcal{N}(A_{OLS}, k_A \times V(A_{OLS})) )</td>
<td>( k_A = 4 )</td>
</tr>
<tr>
<td>log ( \sigma_0 )</td>
<td>log volatility</td>
<td>( \mathcal{N}(k_B, \sigma_o \times I_n) )</td>
<td>( k_o = 1 )</td>
</tr>
<tr>
<td>Hyperpar.</td>
<td>VCV</td>
<td>Prior family</td>
<td>Coefficients</td>
</tr>
<tr>
<td>( Q )</td>
<td>Shocks to ( B_t )</td>
<td>( TW(k_Q^0 \times pQ \times V(B_{OLS}), pQ) )</td>
<td>( k_Q = 0.01, pQ = 40 )</td>
</tr>
<tr>
<td>( S_1 )</td>
<td>Shocks to ( A_t )</td>
<td>( TW(k^0_S \times pS_j \times V(A_{OLS}), pS_j) )</td>
<td>( k_S = 0.1, pS_j = j + 1 )</td>
</tr>
<tr>
<td>( W )</td>
<td>Shocks to log ( \sigma_t )</td>
<td>( TW(k^0_W \times pW \times I_n, pW) )</td>
<td>( k_W = 0.01, pW = n + 1 )</td>
</tr>
</tbody>
</table>

**Note:** \( \mathcal{N} \) and \( TW \) denote the normal and independent inverse-Wishart distributions. \( A_{OLS}, V(A_{OLS}), B_{OLS}, V(B_{OLS}) \) are obtained training sample OLS.

### 4 Results

It is considered that the oil market movements (i.e., global supply and global and oil-specific demand shocks) are the main source of changes in oil prices \( (O_t) \), while the TV standard deviation of the identified \( O_t \), measures the shocks (unexpected movements) originated by other turmoils like wars or unobserved expectations.

We consider that the vector of observed endogenous variables, \( y_t \), includes the log of nominal exchange rate \( \mathcal{E}/USD \) \( (ER_t) \) and the log of nominal Brent price in USD per barrel \( (O_t) \), that is, \( y_t = [ER_t, Ot] \). In order to assess the effects of oil price shocks on the nominal exchange rate, we consider that oil prices are not contemporaneously affected by exchange rate, but the former has an immediate impact on the latter.\(^{10}\)

\(^{10}\)Similar results are found by using \( y_t = [O_t, ER_t]' \). These results are available from the authors upon request.
We select two lags \((k = 2)\) based on Akaike information criteria in the reduced form VAR (time-invariant) model. This is consistent to other studies of the related literature, which use daily data \cite{Fratzscher2014} and with the arguments on short-lived effects of \(O_t\) changes on \(ER_t\) changes at the daily frequency \cite{Ferraro2015}. The simulations are based on 10000 iterations for the Gibbs sampling and 2000 burn-in steps to initialize the sampler. The length of the training sample used for determining prior parameters via least squares is 40.

We first assess the TV standard deviation of the identified oil price shocks, which measures the relative importance of the shocks (unexpected movements) originated by other turmoils like wars or unobserved expectations. Figure 3 displays the posterior mean and the 16th and 84th percentiles of the TV standard deviation of the exchange rate and oil price shocks. On the one hand, the bottom of the Figure 3 shows the posterior mean of the residuals of the oil price equation, the confidence interval and the seven oil price shocks shown in Table 1. We can extract from this Figure some interesting features.

1. It confirms the great volatility of the unexpected movements of oil prices over the whole period. In fact, the peaks in the residuals correspond with the seven oil price shocks.

2. The sharpest peak of variance in 1990 during the Gulf War after the invasion of Kuwait (shock #1) could be explained by the high uncertainty related with the precautionary demand \cite{Kilian2009}.

3. The second highest variance of oil price shocks corresponds to the Great crisis, which means that the world oil price in this period was driven mainly by increased uncertainty.

4. The longest shock, shock #4, was characterized by the low uncertainty in demand shock. In other words, the non-market shocks played a marginal role during this period.

5. The volatility of oil price shocks remains largely affected by uncertainty.

In general, these shocks are consistent with the oil-specific demand shocks depicted in \cite{Kilian2009}, which would be related with higher uncertainty of the precautionary demand for oil. On the other hand, the top of the Figure 3 shows the posterior mean of the residuals of the exchange rate equation. The variance of exchange rates is fairly stable, with the remarkable exception observed during the “Great crisis”.

Figure 4 displays the impulse responses (IRs) of exchange rates and oil prices during the seven shocks described in Table 1. The shadows represent the confidence interval for one standard deviation. As the exchange rate and oil price are used in logs instead of levels, the coefficients can be interpreted as elasticities.

\footnote{Under normality, the 16th and 84th percentiles correspond to the bounds of a one-standard deviation confidence interval.}
Figure 3: Posterior mean, 16th and 84th percentiles of standard deviations of the residuals of the exchange rate €/US$ equation and the residuals of the brent equation. $y_t = (ER_t, O_t)'$. 

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All the IRs of $O_t$ appear to be statistically significant for short periods, between 1 to 10 days, although the oil price shocks with the highest peaks during the Gulf War of 1990 and the great crisis of 2008 (shocks #1 and #5) seem to have responses beyond 10 days.

Figure 5 shows the IRs of the exchange rates and oil prices at the beginning of each year between 1987 and 2016. The IRs are quite substantial and positive around 2000. In the rest of the periods, the IRs tend to be small and negative. On the other hand, the IR for exchange rates are quite small and negative in all the periods, excluding the recent period of 2015 and 2016.

[To be completed]

5 Conclusions

This paper applies Gibbs sampling algorithm to estimate the TV-VAR for oil prices and exchange rates. Based on the work by Primiceri (2005), we allow both coefficients and VCV matrix to change over the time and we estimate TV-VAR using daily data of exchange rate $\text{€}/\text{USD}$ and the oil prices from 1987 to 2017. We find correspondence between the variance of the residuals in oil prices and seven episodes of oil price shocks. In particular, the oil price shocks with higher uncertainty, i.e. during the Gulf War in 1990 and the great crisis in 2008, have shown sharp spikes in the variance of oil price residuals. In any case, we observe that the volatility in the residuals of oil prices has remained high since 1987. Otherwise, the volatility in the residuals of exchange rate is relatively flat.

Likewise, the impulse responses in the spikes of 1990 and 2008 are significant up to 10 days ahead. Moreover, we find negative IR of oil price shocks, excluding the period around 2000.

[To be completed]
Figure 4: Impulse responses analysis during peaks of 7 crisis depicted in Table 1.
Figure 5: Impulse responses analysis for December, 1987-2015
Acknowledgements

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

References


