

Oil Price Forecastability and Economic Uncertainty

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Abstract

Information on economic policy uncertainty (EPU) does matter in predicting oil returns especially when accounting for omitted nonlinearities in the relationship between these two variables via a time-varying coefficient approach. In this work, we compare the forecastability of standard, Bayesian and TVP-VAR models against the random-walk and benchmark AR models. Our results indicate that over the period 1900:1-2014:2 the time-varying VAR model with stochastic volatility outranks all alternative models.

JEL Classification: C22, C32, C53, E60, Q41

Keywords: Oil prices, economic policy uncertainty, forecasting

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1 Introduction

Hamilton (2008) indicates that nine out of ten recessions in the US since World War II have been preceded by an increase in oil prices. Interestingly, Hamilton (2009) goes as far as arguing that a large proportion of the recent downturn in the US GDP during the 'Great Recession' can be attributed to the oil price shock of 2007-2008. Stock and Watson (2003) also show the ability of oil price in predicting growth and inflation. A recent strand of literature emphasizes the role of economic policy uncertainty (EPU) on real activity (Bloom, 2009; Jones and Olson, 2013), which in turn affects oil-price movements, as depicted in Kang and Ratti (2013a, b) and Antonakakis *et al.* (2014). To the best of our knowledge, this is the first attempt to forecast oil returns using a news-based measure of EPU. This measure, developed by Baker *et al.*, (2013), relies on an automated text-search process of large US newspapers and identifies articles that use words related to economic policy, regulation and uncertainty. In our approach we compare the ability of VAR, standard Bayesian VARs and time-varying parameter VARs, against random-walk and univariate AR models of real oil returns over the monthly out-of-sample period 2007:1-2014:2, using an extended in-sample period of 1900:1-2006:12. The paper is organized as follows: section 2 briefly presents the various econometric models and section 3 discusses the data and results; finally section 4 concludes.

2 Econometric Models

The econometric models used include the classical and Bayesian VAR, a time-varying VAR with stochastic volatility (TVP-VAR) and a new TVP-VAR with Markov-switching heteroscedasticity as in Bekiros and Paccagnini (2014). Our benchmark models are the random-walk (RW) and an AR(p) model.

2.1 Classical VAR

As suggested by Sims (1980) it has the following compact format

$$\mathbf{Y}_t = \mathbf{X}_t \boldsymbol{\Phi} + \mathbf{U} \quad (1)$$

where \mathbf{Y}_t is a $(T \times n)$ matrix with rows Y_t' , \mathbf{X} is a $(T \times k)$ matrix ($k = 1 + np, p = \text{number of lags}$) with rows $X_t' = [1, Y_{t-1}', \dots, Y_{t-p}']$. \mathbf{U} is a $(T \times n)$ matrix with rows u_t' , $\boldsymbol{\Phi}$ is a $(k \times n) = [\Phi_0, \Phi_1, \dots, \Phi_p]'$, while the one-step ahead forecast errors u_t have a multivariate $N(0, \boldsymbol{\Sigma}_u)$ conditional on past observations of \mathbf{Y} . Based on the Akaike information criterion the optimal lag p is set at 6.

2.2 BVAR model

A Bayesian VAR (BVAR) imposes restrictions on the numerous VAR parameters by specifying normal prior distributions with zero means and small standard deviations for all coefficients, with a decreasing standard deviation as the lags increase. Popular priors are the "Minnesota" ones, written as follows

$$\Phi_i \sim N(1, \sigma_{\Phi_i}^2) \text{ and } \Phi_j \sim N(0, \sigma_{\Phi_j}^2), \quad (2)$$

where Φ_i denotes the coefficients associated with the lagged dependent variables in each equation of the VAR, while Φ_j represents any other coefficient. The prior variances $\sigma_{\Phi_i}^2$ and $\sigma_{\Phi_j}^2$ specify the uncertainty of the prior means, $\Phi_i = 1$ and $\Phi_j = 0$, respectively. In this study, since our variables are mean-reverting, we impose $\Phi_i = 0$ as well, i.e., a white-noise mean prior. The specification of the standard deviation of

the distribution of the prior imposed on variable j in equation i at lag m , for all i, j and m , denoted by $S(i, j, m)$, is specified as follows

$$S(i, j, m) = [w \times g(m) \times F(i, j)] \frac{\hat{\sigma}_i}{\hat{\sigma}_j}, \quad (3)$$

where

$$F(i, j) = \begin{cases} 1 & \text{if } i = j \\ k_{ij} & \text{otherwise, } 0 \leq k_{ij} \leq 1 \end{cases} \quad (4)$$

is the tightness of variable j in equation i relative to variable i and by increasing the interaction, i.e. it is possible for the value of k_{ij} to loosen the prior. The term w measures the standard deviation on the first lag, and also indicates the overall tightness. The function $g(m) = m^{-d}$, $d > 0$ is the measurement of the tightness on lag m relative to lag 1, and is assumed to have a harmonic shape with a decay of d , which tightens the prior on increasing lags. Following the literature on the Minnesota prior settings, we experimented with various combinations (0.3, 0.5; 0.1, 1.0; 0.2, 1.0; 0.2, 2.0; 0.1, 2.0) of w and d respectively, with k_{ij} set equal to 0.5. We found that $w = 0.3$ and $d = 0.5$ produced the best out-of-sample forecast on average, and hence, we only report the results based on this prior setting for the BVAR.

2.3 TVP-VAR model

As evidenced in D'Agostino *et al.* (2013), a VAR with time-varying parameters and stochastic volatility can predict well many US macroeconomic variables. To model oil price and uncertainty, we implement the following set up:

$$\mathbf{Y}_t = c_t + \sum_{j=1}^K \mathbf{B}_t \mathbf{Y}_{t-j} + \Omega_t^{1/2} \varepsilon_t, \quad (5)$$

where the VAR coefficients $\Phi_t = \text{vec}(\{c_t, B_t\})$ evolve as random walks, $\Phi_t = \Phi_{t-1} + \eta_t$. Following Cogley and Sargent (2005), the covariance matrix of the innovations v_t (Ω_t) can be factored as:

$$\Omega_t = \mathbf{A}_t^{-1} \mathbf{H}_t (\mathbf{A}_t^{-1})' \quad (6)$$

where

$$\mathbf{A}_t = \begin{bmatrix} 1 & 0 \\ \alpha_{21,t} & 1 \end{bmatrix} \text{ and} \\ \mathbf{H}_t = \begin{bmatrix} h_{1,t} & 0 \\ 0 & h_{2,t} \end{bmatrix},$$

with $h_{i,t}$ evolving as geometric random walks: $\ln h_{i,t} = \ln h_{i,t-1} + \tilde{\nu}_t$. We assume that the non-zero and non-one elements of the matrix A_t is a RW such as $\alpha_{21,t} = \alpha_{21,t-1} + \tau_t$. The model is estimated allowing for stochastic volatility in η_t , as suggested in Baumeister *et al.* (2013) and Cogley *et al.* (2008). In this last case, Barnett *et al.* (2014) evidence how the VAR coefficients may change faster during the recent crisis, while the changes are small in tranquil periods, hence the TVP-VAR is a better forecasting tool during turmoil events. We estimate the model using a Gibbs sampling algorithm and the posterior simulated is computed as proposed by Carter and Kohn (2004).

2.4 TVP-VAR model with Markov-Switching Heteroscedasticity

We utilize the multivariate state-space TVP-VAR model of Bekiros and Paccagnini (2014) with h_t the error of the *measurement* equation and Q_t the covariance matrix of the *state* equation. Both equations incorporate time varying coefficient and state transition matrices. As an alternative to the classical TVP-VAR with homoskedastic volatility (stochastic or not) they assume that the measurement and state equation error structure is dependent on unobserved discrete-time, discrete-state Markov processes (TVP-VAR-MS). To estimate the model they introduce a Quasi-optimal Kalman filtering approach with two-state Markov-switching heteroskedasticity. Their set-up is intended to capture a low- and high-volatility regime, as observed in prior and post-crisis periods. They consider the following first-order, ω -state Markov-switching model of heteroskedasticity:

$$\begin{aligned} Q_t &= Q^{S_t} = Q_1\Theta_{1t} + Q_2\Theta_{2t} + \dots + Q_\omega\Theta_{\omega t} \\ h_t &= h^{S_t} = h_1\Theta_{1t} + h_2\Theta_{2t} + \dots + h_\omega\Theta_{\omega t} \\ p &= \begin{pmatrix} p_{11} & p_{12} & \dots & p_{1\omega} \\ p_{21} & p_{22} & \dots & p_{2\omega} \\ \vdots & \vdots & \ddots & \vdots \\ p_{\omega 1} & p_{\omega 2} & \dots & p_{\omega\omega} \end{pmatrix} \end{aligned} \quad (7)$$

where $\Theta_{jt} = 1$ if $S_t = j$ and $\Theta_{jt} = 0$ if $S_t \neq j$ ($j = 1, 2, \dots, \omega$), $p_{ij} = \Pr[S_t = j | S_{t-1} = i]$, for $i, j = 1, 2, \dots, \omega$, and $\sum_{j=1}^{\omega} p_{ij} = 1$. The unobserved-state variable S_t evolves according to a Markov process with the transition probability matrix. In particular for a two-state Markov-switching model of heteroskedasticity: $\Pr[S_t = 1 | S_{t-1} = 1] = P_{11}$; $\Pr[S_t = 0 | S_{t-1} = 1] = 1 - P_{11}$; $\Pr[S_t = 1 | S_{t-1} = 0] = 1 - P_{00}$; $\Pr[S_t = 0 | S_{t-1} = 0] = P_{00}$. They estimate the hyperparameters via an approximated conditional log-likelihood function and show how prediction and smoothing can be obtained. The decoupling of the Kalman filter is derived as

$$\mathbf{y}_t = (\mathbf{z}'_t \otimes \mathbf{I}_N) \boldsymbol{\alpha}_t + \boldsymbol{\varepsilon}_t, \text{ with } \text{Var}(\boldsymbol{\varepsilon}_t) = \text{Var}(h_t^j) \boldsymbol{\Sigma}_* = \boldsymbol{\Sigma}_{h^j} \boldsymbol{\Sigma}_* \quad (8)$$

$$\boldsymbol{\alpha}_t = (\mathbf{T}_t \otimes \mathbf{I}_N) \boldsymbol{\alpha}_{t-1} + (\mathbf{R}_t \otimes \mathbf{I}_N) \boldsymbol{\eta}_t, \text{ with } \text{Var}(\boldsymbol{\eta}_t) = \text{Var}(Q_t^j) \otimes \boldsymbol{\Sigma}_* = \boldsymbol{\Sigma}_{Q^j} \otimes \boldsymbol{\Sigma}_* \quad (9)$$

where $\text{Var}(\boldsymbol{\varepsilon}_t) = \text{Var}(h_t^j) = \boldsymbol{\Sigma}_{h^j}$ and $\text{Var}(\boldsymbol{\eta}_t) = \text{Var}(Q_t^j) = \boldsymbol{\Sigma}_{Q^j}$ are block diagonal matrices, although a more general formulation does not constrain them to be diagonal. However, restrictions are needed on the matrices for the model to be identifiable. The technical specificities of the model can be found in Bekiros and Paccagnini (2014). Finally, prediction is produced via $\mathbf{P}_{t+1|t}^{(i,j)*} = \mathbf{P}_{t+1|t}^{(i,j)} \otimes \boldsymbol{\Sigma}_*$, where $\mathbf{P}_{t+1|t}^{(i,j)}$ is the MSE matrix from the corresponding univariate model.

3 Data and Results

The two variables of concern comprise real oil prices obtained by dividing the Western Texas Intermediate (WTI) by the Consumer Price Index (CPI), and EPU. Standard unit root tests indicate that the log-EPU is stationary as opposed to the logarithm of real oil price, hence the latter is transformed to real oil returns (month-on-month growth rate of real oil price) to ensure mean-reversion. In order to further rationalize the use of TVP-VARs we employed the BDS test (Brock *et al.*, 1996) which overwhelmingly rejected the null hypothesis that AR- or VAR-filtered errors are *i.i.d* for all possible dimensions, thus implying an omitted

nonlinear structure.¹

Table 1: Root Mean Square Errors of Real Oil Returns (2007:1-2014:2)

h	RW	AR	VAR	BVAR	TVP-VAR	TVP-VAR-MS
1	10.1183	0.8490	0.8437	0.8428	0.2476*(*)	0.8982
2	10.1960	0.8361	0.8336	0.8340	0.2095*(*)	0.8378
3	12.3897	0.7013	0.7001	0.7005	0.5662*(*)	0.7250
4	12.9333	0.6746	0.6730	0.6735	0.5467*(*)	0.7100
5	13.6891	0.6398	0.6375	0.6381	0.4650*(*)	0.6517
6	14.7744	0.5961	0.5921	0.5930	0.4795*(*)	0.5932
7	14.1876	0.6326	0.6306	0.6311	0.5277*(*)	0.6248
8	13.8192	0.6518	0.6512	0.6514	0.5083*(*)	0.6422
9	13.4794	0.6729	0.6733	0.6732	0.4913*(*)	0.6507
10	13.3569	0.6784	0.6786	0.6785	0.4721*(*)	0.6673
11	13.4487	0.6756	0.6757	0.6756	0.4504*(*)	0.6600
12	12.8896	0.7040	0.7039	0.7039	0.4714*(*)	0.6938
13	13.7027	0.6665	0.6664	0.6664	0.6174*	0.6450
14	14.0264	0.6555	0.6555	0.6555	0.5882*(#)	0.6325
15	14.0290	0.6595	0.6592	0.6593	0.6200*	0.6316
16	13.5331	0.6837	0.6834	0.6834	0.6600*	0.6785
17	13.1287	0.7077	0.7074	0.7074	0.6672*	0.6731
18	13.3066	0.6976	0.6973	0.6974	0.6497*	0.6722
19	12.7567	0.7311	0.7308	0.7308	0.6987*	0.6980
20	13.6419	0.6887	0.6886	0.6886	0.6373*	0.6602
21	12.4713	0.7481	0.7478	0.7479	0.6855*	0.7177
22	13.3449	0.6967	0.6967	0.6967	0.6383*	0.6854
23	12.6627	0.6794	0.6794	0.6794	0.6954*	0.7314
24	13.6014	0.5859	0.5859	0.5860	0.6866*	0.6851
Average		0.6880	0.6872	0.6873	0.5533	0.6861

Notes: Entries for the RW model are the RMSEs in percentage, while rest of the entries are the relative RMSEs with respect to the RW; * (* or #) indicates significance of the $MSE - F$ statistic with respect to the RW (AR) model at 1% (1% or 5%) level of significance.

We analyze the ability of the EPU to forecast real oil returns over the period 2007:1-2014:2, i.e., during the recent global crisis, using an in-sample period spanning 1900:1-2006:12. All the models are estimated recursively over the out-of-sample period to produce 1- to 24-months-ahead RMSEs. In Table 1, we report the RMSEs from the RW whilst the rest of the models are reported relative to the RW. Based on the results, we can draw the following conclusions: (a) all models outperform the RW at all horizons; (b) on average, the TVP-VAR model with stochastic volatility is the best performer followed by the TVP-VAR-MS; (c) in specific horizons, the TVP-VAR produces the maximum gain at 1- to 18- and 20- to 22-steps-ahead, while the TVP-VAR-MS is the best for the 19-month-ahead and the AR model at 23- and 24-steps-ahead; (d) finally, using the $MSE - F$ test statistic of McCracken (2007) we confirm that the TVP-VAR model statistically outperforms the RW at 1% significance level at all horizons ² and the AR model at horizons of 1- to 12-steps-ahead (1% level) and 14-months (5%). Overall, information on EPU helps in forecasting real oil returns when allowing for adaptive learning or inherent nonlinearities as captured by the TVP-VARs ³

¹Details are available upon request from the authors.

²This test compares the null of equal forecasting ability between a restricted (RW or AR) and an unrestricted model (in our case the best performing VAR on average, i.e., TVP-VAR). For all the other models, the $MSE - F$ is significant at least at the 5% level over all horizons. Complete details are available upon request from the authors.

³The TVP-VAR-MS allows for regime shifts, yet the particular out-of-sample period does not incorporate various regimes but only one i.e., the crisis period. Qualitatively similar results were obtained when we used other periods based on identified structural breaks by the Bai and Perron (2003) tests e.g., 1986:9 or 1999:1, the latter corresponding to the introduction of the euro.

4 Conclusions

The importance of oil prices in determining movements of US growth and inflation is well-established, hence accurate forecasting is of paramount importance. Moreover, recent works in the literature advocate in favor of economic policy uncertainty driving oil-price fluctuations. Against this backdrop, we compare the forecastability of various uni- and multivariate models of real oil returns and EPU. Our results indicate that TVP-VARs outperform the others in all horizons till two-years-ahead relative to the benchmark Random Walk. Consequently, information on EPU does matter in predicting oil returns out-of-sample, especially when accounting for adaptive nonlinearities in the relationship between these two variables via a time-varying coefficient approach.

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