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***Highlights (for review)**

OIL PRICE FORECASTABILITY AND ECONOMIC UNCERTAINTY

- Information on economic policy uncertainty matters in predicting oil price changes
- Nonlinearities are revealed in their relationship via a TVP-VAR approach
- We compare the forecastability of VAR models vs. benchmark AR & RW models
- The results indicate that TVP-VAR models outperform other alternatives

*Title Page

Oil Price Forecastability and Economic Uncertainty

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Abstract

Information on economic policy uncertainty does matter in predicting the change in oil prices. We compare the forecastability of standard, Bayesian and time-varying VAR against univariate models. The time-varying VAR model outranks all alternative models over the period 2007:1 – 2014:2.

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), which in turn affects oil-price movements, as depicted in Kang and Ratti (2013). To the best of our knowledge, this is the first attempt to forecast the change in oil prices 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 changes in oil prices 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

The standard VAR 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 = 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 $(k \times n) = [\Phi_0, \Phi_1, \dots, \Phi_p]'$. In our study we consider that errors u_t follow a multivariate $N(0, \boldsymbol{\Sigma}_u)$ distribution 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 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 models

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 $\Phi_t = \text{vec}(\{c_t, \mathbf{B}_t\})$ 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 $\Omega_t = \mathbf{A}_t^{-1} \mathbf{H}_t (\mathbf{A}_t^{-1})'$ 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 $\mathbf{A}_t$ 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). 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). Moreover, we utilize the TVP-VAR model of Bekiros and Paccagnini (2014) with h_t the *measurement* error and Q_t the covariance matrix of the *state* equation, as an alternative to the classical TVP-VAR with homoskedastic volatility (stochastic or not). They assume that error structure is dependent on unobserved discrete-state Markov processes (TVP-VAR-MS). To estimate it they introduce a Quasi-optimal Kalman filtering approach and consider the following ω -state MS model of heteroskedasticity:

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

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 2x2 Markov transition probability matrix. They estimate the hyperparameters via an approximated conditional log-likelihood function, while the decoupling of the Kalman filter is derived as

$$\begin{aligned}
 \mathbf{Y}_t &= (\mathbf{z}'_t \otimes \mathbf{I}_N) \boldsymbol{\alpha}_t + \boldsymbol{\varepsilon}_t, \text{ with } \text{Var}(\boldsymbol{\varepsilon}_t) = \text{Var}(h_t^j) \boldsymbol{\Sigma}_* = \boldsymbol{\Sigma}_{h^j} \boldsymbol{\Sigma}_* \\
 \boldsymbol{\alpha}_t &= (\mathbf{T}_t \otimes \mathbf{I}_N) \boldsymbol{\alpha}_{t-1} + (\mathbf{R}_t \otimes \mathbf{I}_N) \boldsymbol{\eta}_t, \text{ with } \text{Var}(\boldsymbol{\eta}_t) = \text{Var}(Q_t^j) \otimes \boldsymbol{\Sigma}_* = \boldsymbol{\Sigma}_{Q^j} \otimes \boldsymbol{\Sigma}_*
 \end{aligned} \tag{6}$$

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 usually block diagonal matrices. 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. We analyze the ability of the EPU to forecast real oil price changes over the period 2007:1-2014:2, i.e., during the recent global crisis, using an in-sample period spanning 1900:1-2006:12. Data is obtained from the Global Financial Database. The EPU variable is based on two overlapping sets of newspapers (e.g., Wall Street Journal, NY Times, LA Times, SF Chronicle etc.) within 1900-1985 and 1986-2012. To construct the index, month-by-month searches of each paper is performed for terms related to "economy" and "policy uncertainty".¹ 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 price changes (month-on-month growth rate of real oil price) to ensure mean-reversion. 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.²

INSERT TABLE 1

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

¹Baker *et al.* (2013) searches for articles containing terms such as "uncertainty", "industry" etc. as well "legislation", "regulation" among others. Each article must include terms in all pursued categories pertaining to uncertainty and policy. Further details can be found at:

http://www.policyuncertainty.com/us_historical.html

²Details are available upon request from the authors.

confirm that the TVP-VAR model statistically outperforms the RW at 1% significance level at all horizons³ and the AR model at horizons of 1- to 12-steps-ahead (1% level) and 14-months (5%). Figure 1 depicts the TVP-VAR forecasts for the real oil prices. It is shown that the model captures fluctuations better in “normal” than crisis periods. We also quantify the % gain of the TVP-VAR model over the RW model. Specifically, it is measured around 75% vs. the RW at 1-step-ahead, nearly 80% for 2-steps-ahead whilst it declines to approximately 31% at the end of the horizon (2 years). Overall, information on EPU helps in forecasting real oil price changes when allowing for adaptive learning or inherent nonlinearities as captured by the TVP-VARs⁴.

INSERT FIGURE 1

Note: The black solid line represents the actual oil price level, while the red, blue and yellow lines display the out-of-sample predictions for 1-, 12- and 24-months-ahead

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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³This 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.

⁴The TVP-VAR-MS allows for various regime shifts, yet the particular out-of-sample period incorporates only one i.e., the crisis period. Qualitatively similar results were obtained when we used other periods based on identified structural breaks e.g., 1986:9 or 1999:1, the latter corresponding to the introduction of the euro.

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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.

Figure1

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