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Abstract: There are a large number of models developed in the literature to analyze and forecast the changes in output dynamics. The objective of this paper is to compare the forecasting ability of uni- and bivariate models in terms of forecasting U.S. GNP growth at different forecasting horizons, with the bivariate models containing information on a measure of economic uncertainty. Based on point and density forecast accuracy measures, as well as the superior predictive ability (SPA) and equal accuracy tests, we evaluate the forecasting performance of our models over the quartery period of 1919:2-2014:4, given an in-sample of 1900:1-1919:1. We find that the economic policy uncertainty index should be improve the accuracy of U.S. GNP growth forecasts in the bivariate models. While we find that the Markov-switching time varying parameter VAR (MS-TVP-VAR) models in most cases cannot be outperformed its competitive models according to the root mean squared error (RMSE), the density forecast measure reveals that the Bayesian VAR (BVAR) model with stochastic volatility in most cases is the model that produces more accurate forecasts. More importantly, our results highlight the importance of uncertainty in forecasting US GNP growth rate.

Keywords *Forecast comparison, vector autoregressive models, US GNP, Economic Policy Uncertainty*

JEL classification C22, C32, E32, E37

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1 Introduction

Theoretical papers by Bloom (2009), Mumtaz and Zanetti (2013) and Carriero et al. (2015), following on the early works of Bernanke (1983), Dixit and Pindyck (1994), confirm that, besides productivity and/or policy shocks, various forms of policy generated uncertainty leads to business cycle fluctuations. While, the (negative) influence of uncertainty on economic activity is well-established theoretically, in the wake of the "Great Recession", the focus has also been to quantify the impact of uncertainty. Understandably, this requires a measure of uncertainty - an otherwise latent variable. In this regard, two approaches exist in measuring uncertainty: (1) The news-based approach of Brogaard and Detzel (2015) and Baker et al. (2016), whereby the authors perform month-by-month searches of newspapers for terms related to economic and policy uncertainty to construct their measure of economic policy uncertainty (EPU); (ii) Alternatively, Mumtaz and Zanetti (2013), Mumtaz and Surico (2013), Alessandri and Mumtaz (2014), Mumtaz and Theodoridis (2015, 2016), Bali et al. (2015), Carriero et al. (2015), Chuliá et al. (2015), Jurado et al. (2015), Ludvigson et al. (2015), Rossi and Sekhposyan (2015), Rossi et al. (2016), Shin and Zhong (2016), Creal and Wu (ming) recover measures of uncertainty from the estimation of various types of small- and large-scale structural models related to macroeconomics and finance. Irrespective of whichever approach (news- or model-based) is pursued, these studies along with other studies that have used these indices (for example, Bachmann and Bayer (2011), Knotek II and Khan (2011), Bachmann et al. (2013), Colombo (2013), Jones and Olson (2013), Benati (2013), Caggiano et al. (2014), Kang et al. (2014), Karnizova and Li (2014), Castelnuovo et al. (2015), Cheng et al. (2016), and Balcilar et al. (2016) confirm the evidence of significant role of uncertainty in affecting economic activity).

However, barring the works of Karnizova and Li (2014), and Balcilar et al. (2016), all the above-mentioned studies trying to link uncertainty with economic activity (for example, measures of output and/or unemployment, investment) have been in-sample analysis. Karnizova and Li (2014) depict the role the news-based EPU of Baker et al. (2016) can play in forecasting US recessions based on probit models. While, Balcilar et al. (2016) highlight that forecasting gains for US recessions can be obtained using mixed-frequency Markov-switching models. Against this backdrop of limited evidence on out-of-sample forecasting of a measure of economic activity, and under the widely held view that importance of variables and models require out-of-sample validation (Campbell, 2008), the objective of our paper is to use a wide-array of univariate and multivariate linear and nonlinear models in analysing the role played by the news-based measure of EPU of Baker et al. (2016) in forecasting US Gross National Product (GNP) growth rate. In our study, we analyze the forecasting performances of the various models considered over the historical quarterly period of 1919:2-2014:4, using an in-sample of 1900:1-1919:1. The decision to use the news-based EPU rather than model-based uncertainty simply emanates from the availability of a measure of uncertainty to be used for forecasting GNP growth over the longest possible sample period covering various phases of the US economic history.

Forecasts of output growth represent an important indicator for the policymakers and financial investors. They reveal information about the current state of the economy and play a key role in formulating appropriate monetary and fiscal policies. As outlooks for the future growth possibilities of the economy, they help financial investors in their investment decision making process. Hence, the need for accurately forecasting the growth rate of the economy cannot be overstated. Given the importance of forecasting economic growth, different powerful uni- and multivariate econometric models have been developed in the literature to provide accurate GDP growth forecasts, especially of the of the vector autoregressive (VAR) variety (cf. Rossi and Sekhposyan, 2010, 2014; Eickmeier et al., 2011; Schumacher, 2011; Chauvet and Potter, 2013; Giannone et al., 2015; Schorfheide and Song, 2015, for an overview of different models for forecasting output growth). This paper considers the baseline ARMA model, the Bayesian VAR (BVAR), the threshold VAR (TVAR), the smooth transition VAR (ST-VAR), two-types of time varying parameter VARs (TVP-VARs), the Markov switching VAR (MSVAR), the unobserved component stochastic volatility (UCSV), the Bayesian VAR with CSV and a Mixed-frequency VAR (MF-VAR) to produce both point and density forecasts of U.S. GNP growth. As discussed in Rossi and Sekhposyan (2010), Bekiros and Paccagnini (2013) and D'Agostino et al. (2013), it is important to model nonlinearities when forecasting US output due to issues of structural instabilities, and also when relating movements of output with uncertainty (Caggiano et al., 2014). Hence, we look at both linear and nonlinear models. And in addition, Herbst and Schorfheide (2012), Barnett et al. (2014), Rossi and Sekhposyan (2014) indicates that it is becoming more and more important to assess the correct specification of uncertainty around models' forecasts. For example, central banks around the world are increasingly concerned about uncertainty around the point forecasts of their target variables, and, in the process, the central bankers want to understand how well models perform in forecasting a range of future values of important macroeconomic variables. In other words, the forecaster needs to look at not only point forecasts, but also analyze density forecasts (Bekiros and Paccagnini, 2015a). Note that, in this paper we basically take an atheoretical approach, however, there is of course theoretical models of forecasting output based on large-scale Keynesian-type models and microfounded Dynamic Stochastic General Equilibrium models (cf. Bekiros and Paccagnini, 2013, 2014, 2015b; Del Negro and Schorfheide, 2012; Del Negro et al., 2016, for detailed reviews in this regard). It must be emphasized that our objective in this paper is not necessarily to contribute to the model sets used in forecasting output growth, but the objective is primarily on forecasting US GNP growth based on existing models, but for the first time, incorporating the role of EPU.

The remainder of the paper is organized as follows: Section 2 presents the data used in our analysis. In Section 3 we describe the different forecasting models used in this study. Section 4 provides the forecasting evaluation methodologies and empirical results are presented in Section 5. Finally, Section 6 concludes.

2 Data

In this study, we use data on the real US GNP and the measure of economic uncertainty covering the period quarterly of 1900:1 to 2014:4 (T=460), with the start and end dates being purely driven by data availability of the EPU. Our data on the nominal GNP and the GNP deflator, with the latter used to deflate the former to yield real values, are derived from two sources. First, the observations covering the period 1900:1-1946:4 are obtained from National Bureau of Economic Research (NBER), available for download at: http://www.nber.org/data/abc/; the actual sources are the tables of quarterly data corresponding to Appendix B of Gordon (1986). To the best of our knowledge, this is the only existing source for the pre-1947 quarterly data on US GNP and GNP deflator, with National Income and Product Account (NIPA) quarterly data series non-existent before 1947. Second, data from 1947:1-2014:4 is sourced from the FRED database of the Federal Reserve Bank of St. Louis. Note that, the dataset compiled by runs till 1983:4, with the base year of the GNP deflator being 1972. Given that nominal GNP and GNP deflator data based on the NIPA are available from 1947:1, we decided to use, for these variables, the FRED database, rather than the Gordon (1986) one, which, in any case, would have ran only till 1983:4. The base year of the GNP deflator for the period 1900:1-1946:4 is updated from 1972 to 2009 to correspond to the base year of the GNP deflator based on the NIPA, so that the real GNP is ultimately in constant 2009 prices. As the focus of the paper is to forecast output growth, we work with quarter-on-quarter changes in the natural logarithms of the real GNP in percentage form. This also ensures that the variable is stationary.

The EPU measure used in this study corresponds to the historical measure of uncertainty for the US economy as developed by Baker et al. (2016). The authors use two overlapping sets of newspapers to create this series. The first spans 1900 - 1985 and is comprised of the Wall Street Journal, the New York Times, the Washington Post, the Chicago Tribune, the LA Times, and the Boston Globe. From 1985 until 2012, we use the previously mentioned newspapers along with USA Today, the Miami Herald, the Dallas Morning Tribune, and the San Francisco Chronicle.

To construct the index, Baker et al. (2016) perform month-by-month searches of each paper, starting in January of 1900, for terms related to economic and policy uncertainty. In particular, they search for articles containing the term ’uncertainty’ or ’uncertain’, the terms ’economic’, ’economy’, ’business’, ’commerce’, ’industry’, and ’industrial’ as well as one or more of the following terms: ’congress’, ’legislation’, ’white house’, ’regulation’, ’federal reserve’, ’deficit’, ’tariff’, or ’war’. In other words, to meet their criteria for inclusion, the article must include terms in all three categories pertaining to uncertainty, the economy and policy.

To deal with changing volumes of news articles for a given paper over time, Baker et al. (2016) divide the raw counts of policy uncertainty articles by the total number of news articles containing terms regarding the economy or business in the paper. They then normalize each paper’s series to unit standard deviation prior to December 2009 and sum each paper’s series. The data is available for download from: https://www.policyuncertainty.com/us_monthly.html. Note that this data is available at monthly frequency, so we compute quarterly values of the series by taking three-months averages to come up with a quarterly value for this index. The monthly value of the index is used for the mixed frequency model of forecasting (discussed below in detail). Standard unit root tests indicated that the natural logarithm of EPU is stationary, and hence, we worked with the series in its log-level form. The data have been plotted in *Fig.* 1.

3 Forecasting Models

In this section we briefly describe the specifications of our uni- and bivariate econometric models used in the forecasting exercises.

3.1 Univariate Models

1. *Autoregressive Moving Average Model:*
   The basic ARMA(p,q) model with constant shock variance is given by

$$x_t = c + \sum_{i=1}^{p} a_i x_{t-i} + \sum_{j=1}^{q} b_j \epsilon_{t-j} + \epsilon_t, \tag{1}$$

   where x_t is the US GNP growth and $\epsilon_t \sim N(0, \sigma)$.

2. *Unobserved Component Model with Stochastic Volatility:*
   Previous studies show that the unobserved component model with stochastic volatility (UCSV) is appropriate to forecast GDP growth and inflation (cf. Barnett et al., 2014; Stock and Watson, 2007). Based on Stock and Watson (2007) the UCSV can be formalized as

$$\begin{aligned} x_t &= \mu_t + \sqrt{\sigma_u} u_t, & u_t &\sim iidN(0, \sigma_u) \\ \mu_t &= \mu_{t-1} + \sqrt{\sigma_v} v_t, & v_t &\sim iidN(0, \sigma_v), \end{aligned} \tag{2}$$

   where x_t is the US GNP growth, the variances σ_u and σ_v follow a stochastic volatility process and $\mu = (\mu_1, \ldots, \mu_T)$ denotes the vector of unobserved states.

3.2 Bivariate Models

1. *Bayesian Vector Autoregressive (BVAR) Model:*
   A baseline VAR(p) model with constant variance-covariance of shocks has the following form

$$x_t = \Phi_1 x_{t-1} + \cdots + \Phi_p x_{t-p} + c + \xi_t, \tag{3}$$

   where x_t is a $T \times 2$ data matrix that contains the GNP growth and logarithmized EPU.

   By defining $z_t = [x'_{t-1}, \ldots, x'_{t-p}, 1]'$ and $\Phi = [\Phi_1, \ldots, \Phi_p, c]'$, the baseline VAR(p) can be expressed as

$$x_t = Z'_t \phi + \xi_t, \tag{4}$$

   where $Z_t = I_n \otimes z_t$, $\phi = vec(\Phi)$, and ξ_t is a vector of Gaussian random variables with covariance matrix Σ. The baseline VAR model is called Bayesian VAR (BVAR) when it is estimated with Bayesian methods (cf. Koop and Korobilis, 2010). Koop and Korobilis (2010) use a variety of priors and estimation methods for BVARs and do not find significant differences in the estimation results. Following Koop and Korobilis (2010) and Del Negro and Schorfheide (2011) we also use Minnesota priors that allows simple posterior and predictive forecasts.

2. *BVAR with Common Stochastic Volatility Model:*
Recent studies by Clark (2011) and Carriero et al. (2015) show that a combination of the BVAR with common stochastic volatilities brings gain in improvement of the forecasting performance of these models. Following Carriero et al. (2015) the BVAR with common stochastic volatility (BVAR-CSV) model can be formulated as

$$\begin{aligned} x_t &= Z_t'\phi + \xi_t, & & \\ \xi_t &= D^{-1} f_t^{0.5} v_t, & & v_t \sim iidN(0, I) \\ \ln f_t &= \psi \ln f_{t-1} + u_t, & & var(u_t) = \phi, \end{aligned} \tag{5}$$

where x_t is a $T \times 2$ data matrix that consists of the GNP growth and logarithmized EPU, D^{-1} is a lower triangular matrix, and f_t is a scalar process.

3. *Threshold VAR Model:*
In contrast to the linear VARs, the threshold VAR (TVAR) model allows for capturing a nonlinear dependence structure between macroeconomic variables (cf. Wolters et al., 1998; Avdjiev and Zeng, 2014) and is defined as follows

$$\begin{aligned} x_t &= \Phi_{11} x_{t-1} + \cdots + \Phi_{1p} x_{t-p} + c_1 + \xi_{1t}, & & var(\xi_{1t}) = \Omega_1 \text{ if } x_{t-d} \le x_1^* \\ x_t &= \Phi_{21} x_{t-1} + \cdots + \Phi_{2p} x_{t-p} + c_2 + \xi_{2t}, & & var(\xi_{2t}) = \Omega_2 \text{ if } x_{t-d} > x_1^*, \end{aligned} \tag{6}$$

where x_t is a $T \times 2$ data matrix that consists of the GNP growth and logarithmized EPU and x_{t-d} denotes d^{th} lag of GNP growth and x_1^* is the threshold level of growth that indicates expansions or recessions. The delay parameter means that if the threshold variable x_{t-d} outruns the threshold level x_1^* at time $t-d$, the dynamics actually change at time t.

4. *Smooth Transition VAR Model:*
The smooth transition VAR (ST-VAR) model has the following form

$$x_t = \sum_{i=1}^{p} \Phi_{1i} x_{t-i} + c_1 + \pi\left(\lambda, x_1^*, x_{t-d}\right)\left(\sum_{i=1}^{p} \Phi_{2i} x_{t-i} + c_2\right) + \xi_t, \tag{7}$$

where x_t is a $T \times 2$ data matrix that consists of the GNP growth and logarithmized EPU and $\pi(\cdot)$ is a logistic transition function that is given by

$$\pi\left(\lambda, x_1^*, x_{t-d}\right) = \left[1 + \exp\left(-\lambda(x_{t-d} - x_1^*)\right)\right]^{-1} \tag{8}$$

with $\lambda > 0$ the smoothing parameter. x_1^* is the threshold value around which the dynamics of the model change.

5. *Markov Switching VAR (MS-VAR) Model:*
One of the merit of the Markov switching VAR model is that it accounts for the possibility of structural shifts in the data. The MS-VAR model is defined as

$$x_t = c_{\delta_t} + \sum_{i=1}^{p} \Phi_{\delta_t} X_{t-i} + \xi_t, \qquad var(\xi_t) = \Omega_{\delta_t}, \tag{9}$$

where x_t is a $T \times 2$ data matrix that consists of the GNP growth and logarithmized EPU and, Φ_{δ_t} and Ω_{δ_t} are regime dependent autoregressive coefficients and variance-covariance matrices. δ_t is a discrete process taking its values in $[1, S]$. δ_t is the latent variable that controls the state of the economy. It can be equal to 1,2,..., or S, with S the number of states in the economy. Here we assume that S is equal to 2. We note that δ_t is a first-order Markov chain that is characterized by the following transition probabilities p_{ij} between the different states of the economy:

$$p(\delta_t = j|\delta_{t-1} = i, \delta_{t-2} = k, \dots) = p(\delta_t = j|\delta_{t-1} = i) = p_{ij}, \text{ with } \sum_{j=1}^{S} p_{ij} = 1, \forall i. \tag{10}$$

6. *Time-Varying Parameter VAR (TVP-VAR) Model:*
By allowing the parameters to change over time, the TVP-VAR represents an appropriate modeling approach that can take into account the economic dynamics that evolve over time (cf. Cogley and Sargent, 2002; Primiceri, 2005 for original contributions to the development of the TVP-VAR model and Nakajima, 2011 for a detailed overview of methodology and empirical applications). Following Del Negro and Schorfheide (2011) the TVP-VAR model can be formalized as

$$x_t = Z_t' \phi_t + \xi_t, \qquad var(\xi_t) = \Sigma_t \tag{11}$$

where x_t is a $T \times 2$ data matrix that consists of the GNP growth and logarithmized EPU and the parameters, ϕ_t, evolve according to the random walk process

$$\phi_t = \phi_{t-1} + e_t, \qquad e_t \sim iidN(0, Q). \tag{12}$$

The covariance matrix Q is restricted to be diagonal and e_t are uncorrelated with ξ_t. The innovations ξ_t are normally distributed with variance covariance matrix Σ_t.

$$\xi_t \sim N(0, \Sigma_t), \qquad \Sigma_t = D_t^{-1} H_t (D_t^{-1})', \tag{13}$$

where D_t is a lower triangular matrix and H_t is a diagonal matrix whose elements, $h_{i,t}^2$ follows a geometric random walk:

$$\ln h_{i,t} = \ln h_{i,t-1} + \eta_t, \qquad \eta_t \sim iidN(0, \sigma_i^2). \tag{14}$$

7. *Markov-switching Time-Varying Parameter VAR (MS-TVP-VAR) Model:*
Now we extend the TVPVAR model to the Markov-switching time-varying parameter VAR (MS-TVP-VAR) model by allowing the time varying parameters to be dependent on an unobservable variable δ_t that controls the state of the economy (cf. Bekiros and Paccagnini, 2013, 2015b, for original contributions to the development of this framework and applications for forecasting). The MS-TVP-VAR has the following form:

$$x_t = Z_t'\phi_{t,\delta_t} + \xi_t, \qquad var(\xi_t) = \Sigma_t, \tag{15}$$

where x_t is a $T \times 2$ data matrix that consists of the GNP growth and logarithmized EPU and ϕ_{t,δ_t} is a time varying regime dependent autoregressive coefficients.

8. *Mixed Frequency VAR (MF-VAR) Model:*
Recently developed by Schorfheide and Song (2015), the MFVAR model is a useful tool that allows the modeling and forecasting of macroeconomic variables with different frequency

$$x_t = \Phi_1 x_{t-1} + \cdots + \Phi_p x_{t-p} + c + \xi_t, \qquad \xi_t \sim iidN(0, \Sigma) \tag{16}$$

where $x_t = [x_{m,t}', x_{q,t}']$. The vector $x_{m,t}$ consists of variables that are observed at monthly frequency, for example the economic policy uncertainty index, and the vector $x_{q,t}$ contains the unobserved monthly variables that are only released quarterly (for example, US GNP growth).

4 Forecasting Evaluation Methodologies

To estimate our portfolio of models and produce forecasts for the time t and beyond we adopt the rolling forecasting scheme. We start with observations from the time period 1900:1 to 1919:1 as in-sample and use those from the period 1919:2 to 2014:4 as out-of-sample. For each iteration we produce U.S. GNP growth forecasts up to 8 quarters ahead. All the models are estimated using the Bayesian Markov Chain Monte Carlo (MCMC) methods. Using a Gibbs Sampler, draws from the posterior distribution can be generated and based on these draws, future trajectories of x_t can be simulated to characterize the predictive distribution related to each model we study here and to calculate point and density forecasts. We evaluate our models using the following univariate criteria.

4.1 Point Forecasts

Root-Mean-Square Error:
The often used and most popular univariate measure of accuracy of point forecasts is the root mean squared error that is defined as

$$\text{RMSE}_h = \sqrt{\frac{1}{n-h}\sum_{t=1}^{n-h}(\hat{x}_{t+h} - x_{t+h})^2}, \tag{17}$$

where $(\hat{x}_{t+h} - x_{t+h})$ is the forecast error and $(n - h)$ denotes the number of evaluated h-step-ahead forecasts.

4.2 Density Forecasts

Log Predictive Density Score:
To evaluate the forecast performance of our models we also use the log predictive density score (LPDS) in Adolfson et al. (2007) that is given by

$$\mathrm{LPS}_h = -2\log p_t(x_{t+h}), \tag{18}$$

where $p_t(x_{t+h})$ is the h-step-ahead forecast distribution of the $n-$dimensional data vector x_{t+h}.

Here we assume that $p_t(x_{t+h})$ follows a Normal distribution and the log predictive density score can be rewritten as

$$\mathrm{LPS}_h = \left(n\log(2\pi) + \log|Q_{t+h|t}| + (x_{t+h} - \bar{x}_{t+h|t})'\, Q^{-1}_{t+h|t}\,(x_{t+h} - \bar{x}_{t+h|t})\right) \tag{19}$$

x_{t+h} is the observed outcome, $\bar{x}_{t+h|t}$ denotes the posterior mean of the forecast distribution and $Q_{t+h|t}$ is the posterior variance of the forecast distribution.

4.3 Superior Predictive Ability Test

Recently developed by Hansen (2005) the superior predictive ability (SPA) test is a modification of the reality check test proposed by White (2000). Based on the framework of the reality check test the SPA test allows to compare the relative performance of a particular model with its competitors via a pre-specified loss function. The null hypothesis that the benchmark (or basis) model is not outperformed by any of the other competitive models can be formalized as follows

$$H_0 : \max_{i=1,\dots,K} \mathbb{E}\left[d_t\right] \leq 0, \tag{20}$$

where $d_t = (d_{i,t}, \dots, d_{K,t})'$ is a vector of relative performances, $d_{i,t}$, that are computed as $d_{i,t} = L^{(0)}_{t,h} - L^{(i)}_{t,h}$. K is the number of the competitive models, h denotes the forecasting horizon and $L^{(0)}_{t,h}$ and $L^{(i)}_{t,h}$ are the loss functions at time t for a benchmark model M_0 and for its competitor models, $M_{i_{(i=1,\dots,K)}}$, respectively.

The test statistic related to the SPA is given by

$$\mathrm{SPA} = \max_{i=1,\dots,K} \frac{\sqrt{T}\bar{d}_i}{\sqrt{\lim_{T\to\infty} \mathbb{V}ar(\sqrt{T}\bar{d}_i)}}, \tag{21}$$

where $\bar{d} = T^{-1}\sum d_t$. A stationary bootstrap procedure is used to obtain the p-values of the SPA.[2]

5 Empirical Study

5.1 Results

With the U.S. GNP growth forecasts we compute for each model specification the root mean squared errors (RMSEs) and the log predictive density scores (LPDS) at different forecasting horizons and the results are reported in Tables 1 and 2, respectively. Except for the STVAR and TVPVAR models the bivariate models in most cases outperform the univariate models. This suggests that the economic policy uncertainty index has information content that helps improving the accuracy of the U.S. GNP growth forecasts. According to the RMSEs the MSTVPVAR seems to be the best model, as it has the lowest RMSE and cannot be outperformed by other competing models. At the 1 quarter forecast horizon forecast the RMSE has its lowest value (2.184) relative to longer horizon forecasts. The highest RMSE is at quarter 5 with a value of 2.734.

Fig. 2 illustrates the forecasts obtained from the MSTVPVAR model for all forecasting horizons (h=1,. . . ,8) and the actual values of the U.S. real GNP growth and *Fig.* 3 depicts those from the BVAR model with stochastic volatility and the actual values of the U.S. real GNP growth. At the 1- and 2- quarter forecast horizons both model provide relatively good forecasting performance. The difference between the forecasts and the actual data for both models are not so pronounced. At the 3 quarter forecast horizon and beyond while we observe that the forecasts from the BVAR model with stochastic volatility sometimes run parallel to the actual data and the deviations from the actual data become larger and larger as the forecast horizon increases, the forecasts from the MSTVPVAR model better approximate the actual data.

According to the log predictive density score (LPDS) at the one-quarter and eight-quarter horizons the BVAR exhibits the smallest LPDS followed by the MSVAR at the two-quarter horizon. The Bayesian VAR model with stochastic volatility (BVARCSV) provides in most cases the most accurate forecasts and improves over other models at the three-quarter up to seven-quarter horizon with the LPDS values being between 4.1 and 4.2. It should be noted that the BVAR and TVAR models have LPDS scores of 4.14 to 4.27 for horizons of 3 to 7 quarter forecast horizon, values close to BVARCSV.

Based on the SPA test results (Table 3) we see that the MSTVPVAR model followed by the TVAR, BVARCSV and BVAR cannot be outperformed by other competing models at the 10% confidence level for all forecasting horizons. At the two-quarter ahead horizon and beyond, the MFVAR and ARMA models also perform well and dominate other models. For the UCSV and the STVAR models the null hypothesis that they cannot be outperformed by other forecasting models is rejected at the 10% level for all forecasting horizons. While the UCSV performs the worst, the baseline ARMA model cannot be rejected at the 10% confidence level at the two-quarter horizon and beyond.

We also compare our best models to the remaining ones and the result are presented in Tables 4 and 5. The pairwise comparison between the MSTVPVAR and other bivariate models (BVAR, TVAR, STVAR, MSVAR, TVPVAR, and MFVAR) based on the root

[2]We refer the reader to Hansen (2005) for more details on technical issues.

mean squared error shows that the forecasts from MSTVPVAR model for the one-quarter ahead horizon up to three-quarter ahead horizon are superior to those of other bivariate models at the 10% confidence level. At the four-quarter horizon and beyond all the bivariate model perform equally well, cf. Table 4.

When applying the equal accuracy test of Diebold and Mariano (1995) to the BVARCSV and the remaining competitive models we obtain a clear superiority of the BVARCSV over the STVAR and TVPVAR at the two-quarter ahead horizon and beyond, the MSTVPVAR for all forecasting horizons and the MFVAR at the one-quarter ahead horizon, cf. Table 5.

6 Conclusion

A large number of models have been employed in the extant literature to analyze and forecast the changes in output growth. The objective of this paper is to compare the forecasting ability of 10 (both uni- and bivariate) models in terms of forecasting U.S. GNP growth at different forecasting horizons, with the bivariate models containing information on a measure of economic uncertainty. We evaluate the forecasting performance of these 10 models over the quarterly period of 1919:2-2014:4. We begin our in-sample period at 1900:1-1919:1 and perform a rolling window forecast exercise over eight quarters. Our results indicate that the economic policy uncertainty index can help improving the accuracy of U.S. GNP growth forecasts in bivariate models based on point and density forecast accuracy measures, as well as the superior predictive ability (SPA) tests and equal accuracy tests.

Based on our model selection criteria (RMSE and LPDS) as well as on the SPA test and the equal accuracy test, we find that the Markov Switching-Time Varying Parameter VAR (MSTVPVAR) model and the Bayesian VAR with stochastic volatility (BVARCSV) model provide accurate U.S. GNP growth forecasts that cannot be outperformed by the other competing models from the literature. More importantly, our results show that the economic policy uncertainty measures can help improving the accuracy of US GNP growth forecasts.

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Table 1: RMSE for uni- and bivariate models

Models	Forecasting horizons							
	1Q	2Q	3Q	4Q	5Q	6Q	7Q	8Q
ARMA	2.601	2.909	2.926	2.969	2.961	2.950	2.939	2.986
UCSV	2.863	3.462	3.421	3.657	3.878	3.786	3.750	3.853
BVAR	2.612	2.884	2.806	2.850	2.914	2.893	2.895	2.895
BVARCSV	2.583	2.852	2.793	2.892	2.943	2.923	2.931	2.942
TVAR	2.632	2.861	2.833	2.893	2.921	2.941	2.935	2.913
STVAR	2.668	7.711	35.826	65.335	128.776	189.233	246.049	301.996
MSVAR	2.608	2.884	2.830	2.883	2.925	2.899	2.909	2.910
TVPVAR	2.749	3.106	3.033	132.711	13.630	60.564	84.944	195.872
MS-TVPVAR	**2.184**	**2.486**	**2.397**	**2.595**	**2.734**	**2.569**	**2.568**	**2.607**
MFVAR	3.088	2.908	2.906	2.916	2.930	2.927	2.936	2.926

Note: The entries are RMSEs. The values in bold correspond to the smallest RMSEs.

Table 2: Density forecasts for uni- and bivariate models

Models	Forecasting horizons							
	1Q	2Q	3Q	4Q	5Q	6Q	7Q	8Q
ARMA	4.125	4.302	4.464	4.614	4.842	5.123	5.547	6.091
UCSV	4.481	4.785	4.979	5.141	5.303	5.423	5.553	5.688
BVAR	**3.942**	4.084	4.161	4.210	4.228	4.228	4.236	**4.234**
BVARCSV	3.979	4.071	**4.080**	**4.091**	**4.199**	**4.046**	**4.230**	4.271
TVAR	3.945	4.120	4.138	4.216	4.248	4.261	4.270	4.276
STVAR	3.989	4.461	4.948	5.405	5.778	5.815	6.197	6.382
MSVAR	4.107	**4.063**	4.204	4.228	4.260	4.263	4.295	4.298
TVPVAR	3.985	4.778	5.240	5.561	5.858	6.048	6.150	6.268
MS-TVPVAR	5.165	6.294	7.492	7.224	6.976	8.975	7.647	7.576
MFVAR	4.255	4.204	4.220	4.231	4.246	4.260	4.266	4.257

Note: The entries are log predictive density scores (LPDS). The values in bold correspond to the smallest LPDS.

Table 3: Results of SPA tests for US-GNP growth forecasts

Basic model	Forecasting horizons							
	1Q	2Q	3Q	4Q	5Q	6Q	7Q	8Q
ARMA	**0.065**	0.223	0.132	0.202	0.508	0.332	0.323	0.228
UCSV	**0.045**	**0.008**	**0.018**	**0.008**	**0.004**	**0.007**	**0.010**	**0.009**
BVAR	0.112	0.293	0.209	0.673	0.791	0.499	0.386	0.416
BVARCSV	0.120	0.291	0.194	0.412	0.524	0.316	0.302	0.354
TVAR	0.079	0.311	0.215	0.446	0.573	0.305	0.288	0.401
STVAR	**0.081**	**0.059**	**0.091**	**0.094**	**0.096**	**0.098**	**0.083**	**0.081**
MSVAR	0.116	0.325	**0.086**	**0.044**	0.695	0.513	0.404	0.313
TVPVAR	**0.035**	**0.050**	**0.074**	0.253	0.116	0.177	0.141	0.200
MSTVPVAR	1.000	0.894	1.000	0.962	0.812	0.913	0.980	0.988
MFVAR	**0.008**	0.202	0.117	0.204	0.639	0.371	0.174	0.364

The entries are the p-values of the SPA test of Hansen (2005) for the pertinent model and criterion. The null hypothesis is that a benchmark model cannot be outperformed by other candidate models. The values in bold face represent the p-values that are smaller than or equal to the 10% confidence level under a pre-specified loss function.

Table 4: Results of equal accuracy tests based on the point forecast measure for US-GNP growth forecasts

Model1	model2	Forecasting horizons							
		1Q	2Q	3Q	4Q	5Q	6Q	7Q	8Q
BVAR	MSTVPVAR	1.979	1.401	1.278	0.774	0.632	1.116	0.930	0.8468
		(0.024)	(0.081)	(0.101)	(0.220)	(0.264)	(0.132)	(0.176)	(0.199)
BVARCSV		1.826	1.196	1.317	0.977	0.869	1.473	1.165	1.138
		(0.034)	(0.116)	(0.094)	(0.165)	(0.193)	(0.071)	(0.122)	(0.128)
TVAR		2.088	1.276	1.344	0.927	0.656	1.261	1.030	0.890
		(0.019)	(0.101)	(0.090)	(0.177)	(0.256)	(0.104)	(0.152)	(0.187)
STVAR		1.767	1.801	1.239	1.168	1.178	1.243	1.324	1.080
		(0.039)	(0.036)	(0.108)	(0.122)	(0.120)	(0.107)	(0.093)	(0.140)
MSVAR		1.983	1.394	1.349	0.875	0.676	1.134	0.958	0.888
		(0.024)	(0.082)	(0.089)	(0.191)	(0.250)	(0.129)	(0.169)	(0.187)
TVPVAR		2.422	1.942	1.728	1.000	1.018	0.999	0.995	0.998
		(0.008)	(0.026)	(0.042)	(0.159)	(0.155)	(0.159)	(0.160)	(0.160)
MFVAR		3.429	1.338	1.590	0.993	0.691	1.259	1.052	0.948
		(0.000)	(0.091)	(0.056)	(0.161)	(0.245)	(0.104)	(0.147)	(0.172)

Note: Table entries are t-statistics and p-values (in parentheses) of the Diebold and Mariano (1995) test. The null hypothesis is that the forecasts at horizon h of model 2 is equal to the one of model 1 against the one-sided alternative that forecasts from model 2 is superior to the one of model 1.

Table 5: Results of equal accuracy tests based on density forecast measure for US-GNP growth forecasts

Model1	model2	Forecasting horizons							
		1Q	2Q	3Q	4Q	5Q	6Q	7Q	8Q
BVAR	BVARCSV	-0.256	0.081	0.522	0.513	0.105	0.795	0.021	-0.101
		(0.601)	(0.468)	(0.301)	(0.304)	(0.458)	(0.213)	(0.491)	(0.540)
TVAR		-0.224	0.255	0.423	0.594	0.184	0.958	0.133	0.016
		(0.589)	(0.400)	(0.336)	(0.276)	(0.427)	(0.169)	(0.447)	(0.494)
STVAR		0.050	1.544	3.166	4.220	4.195	5.060	4.243	3.894
		(0.480)	(0.062)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
MSVAR		0.604	-0.031	0.450	0.439	0.162	0.623	0.141	0.050
		(0.273)	(0.512)	(0.326)	(0.330)	(0.436)	(0.267)	(0.444)	(0.480)
TVPVAR		0.032	2.795	4.229	4.721	4.405	5.727	4.141	3.685
		(0.487)	(0.003)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
MSTVPVAR		5.566	8.794	12.443	10.061	7.377	14.098	7.369	6.098
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
MFVAR		1.295	0.528	0.508	0.448	0.123	0.614	0.078	-0.025
		(0.098)	(0.299)	(0.306)	(0.327)	(0.451)	(0.270)	(0.469)	(0.510)

Note: Table entries are t-statistics and p-values (in parentheses) of the Diebold and Mariano (1995) test. The null hypothesis is that the forecasts at horizon h of model 2 is equal to the one of model 1 against the one-sided alternative that forecasts from model 2 is superior to the one of model 1.

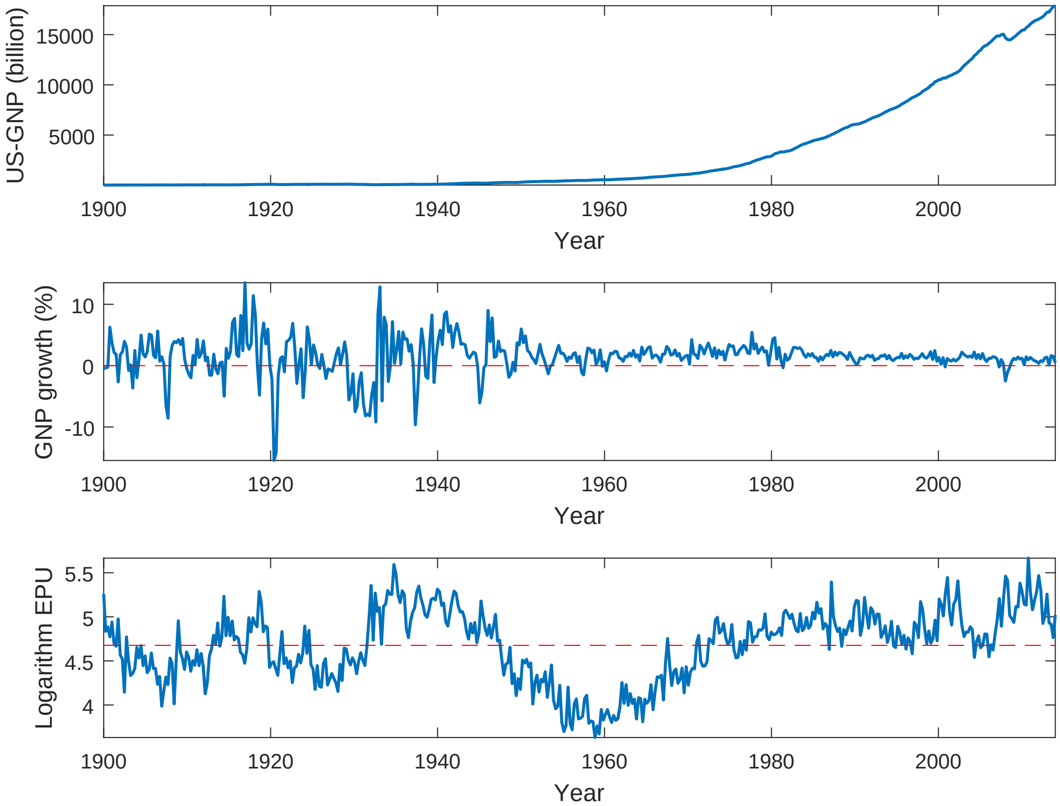

Figure 1: Plot of U.S. real GNP, its corresponding percentage changes, and the logarithmized EPU.

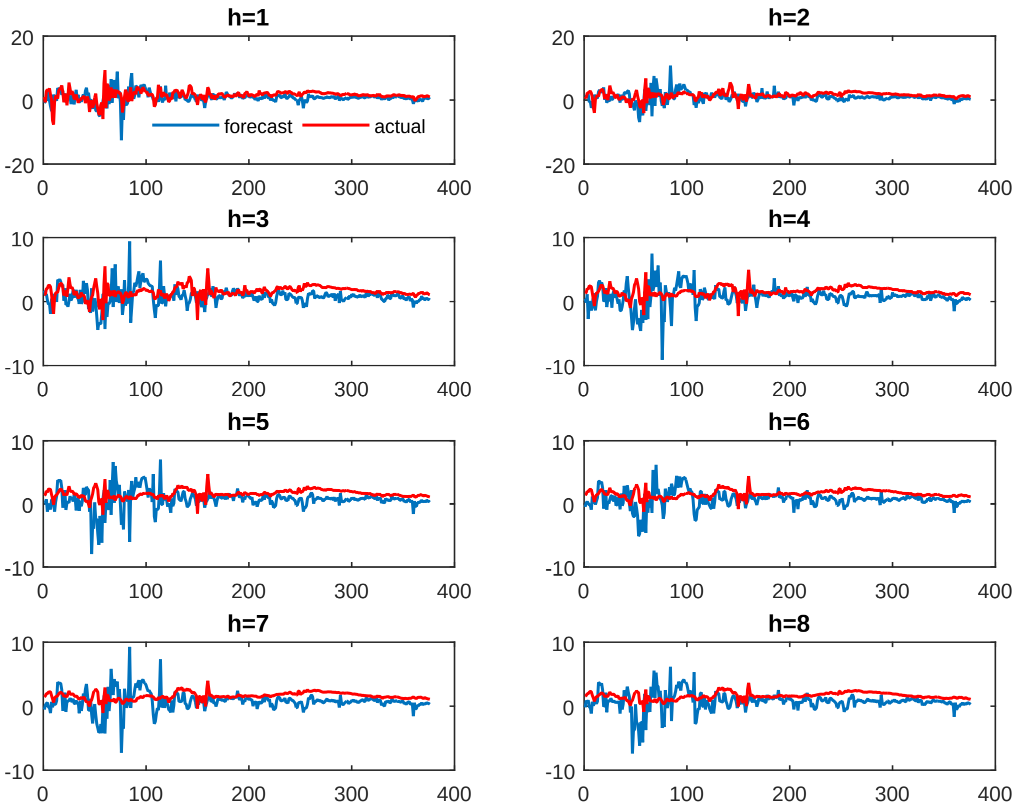

Figure 2: Plot of forecasts obtained from the MSTVPVAR model for different forecasting horizons and the actual real U.S. GNP growth.

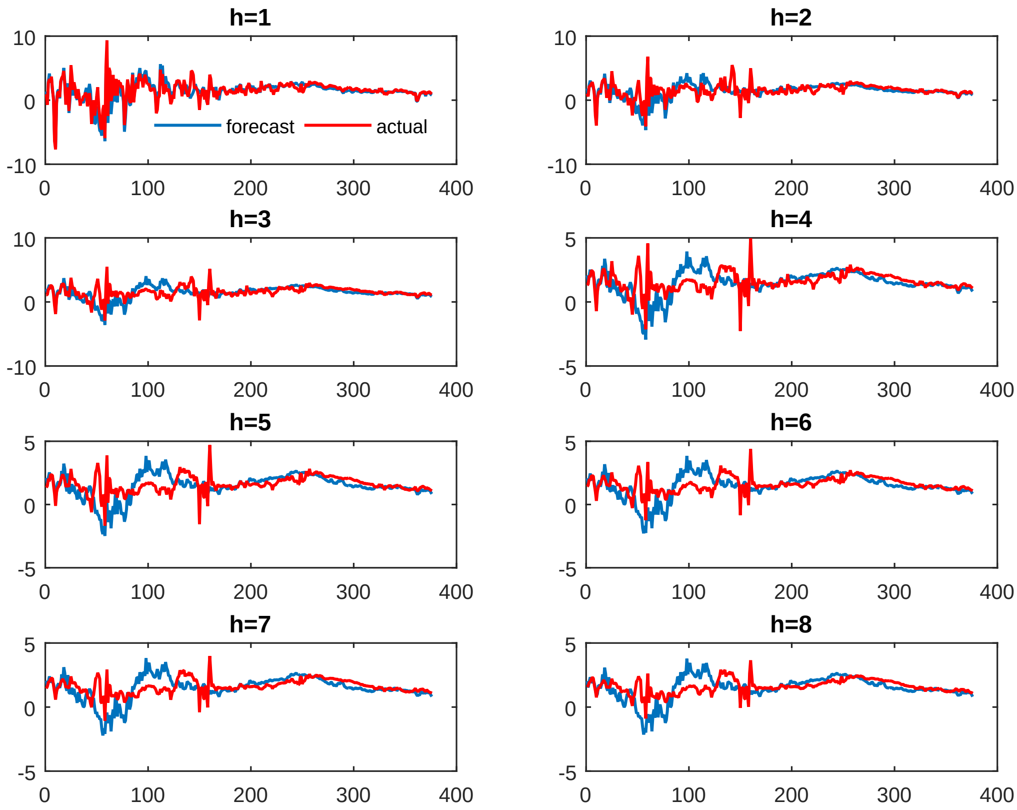

Figure 3: Plot of forecasts obtained from the BVAR model with stochastic volatility for different forecasting horizons and the actual real U.S. GNP growth.