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Rangan Gupta
University of Pretoria
Xiaojin Sun
University of Texas at El Paso
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Department of Economics
University of Pretoria
0002, Pretoria
South Africa
Tel: +27 12 420 2413

Forecasting Economic Policy Uncertainty of BRIC Countries Using Bayesian VARs

Rangan Gupta* Xiaojin Sun †

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Abstract

This paper utilizes the recently developed methods of compressing the parameters and the data for a high-dimensional vector autoregression (VAR) to forecast economic policy uncertainty (EPU) of Brazil, China, India and Russia (BRIC) based on EPUs of additional 18 other developed and developing countries. In line with the recent literature on spillover of EPUs across countries, we show that incorporating information of EPUs of other countries does indeed produce gains in forecasting the EPU of the BRIC bloc, irrespective of whether we compress the parameters or the data.

JEL Classification: C11, C32, C53, C55, E60

Keywords: Economic Policy Uncertainty, VAR, Bayesian Methods, BRIC Countries

*Department of Economics, University of Pretoria, Pretoria, 0002, South Africa. Email: rangan.gupta@up.ac.za.

†Department of Economics and Finance, University of Texas at El Paso, El Paso, TX 79968, USA. Email: xsun3@utep.edu.

1 Introduction

Theoretically, uncertainty is known to negatively impact economic activity by causing delays in investment and hiring decisions of firms, and through the postponement of consumption spending by households in favor of precautionary savings (as discussed in Bernanke (1983), Dixit et al. (1994), and more recently by Bloom (2009)). However, uncertainty is a latent variable and hence, unobservable. But, Baker et al. (2016) has solved this problem by constructing normalized indexes of the volume of newspaper articles discussing economic policy uncertainty (EPU) for a large number of developed and developing economies. Using these news-based measures of uncertainty, empirical validation of the theoretical prediction that heightened uncertainty leads to recessions for both advanced and emerging countries can be found in the recent works of Karnizova and Li (2014), Balcilar et al. (2016), Kurasawa (2017), Junttila and Vataja (2018), Aye et al. (2019a,b), Pierdzioch and Gupta (2017). Despite the well-established importance of uncertainty in macroeconomic developments, both theoretically and now empirically, there is no systematic effort to forecast uncertainty that will allow policymakers to act upon such forecasts while making their decisions in terms of designing appropriate policies ahead of time to deal with future business cycle downturns.

The two studies that we could find are the papers of Wang et al. (2015) and Degiannakis and Filis (2019). In the first paper, the authors successfully forecasted the EPU of the United States (US) using changes in prices of 23 commodities, especially when forecast combination methods were used. The second study concentrated on forecasting EPU in Europe, and showed that global EPU provides the highest predictive gains, followed by European and US stock market realized volatilities, with the European stock market implied volatility index also playing an important role as a predictor.

Against this backdrop of limited number of studies on forecastability of EPUs (and uncertainty in general), and given the widespread evidence of spillovers of EPU across developed and developing economies (see for example, Klößner and Sekkel (2014), Yin and Han (2014), Gupta et al. (2016), Antonakakis et al. (2018), Gabauer and Gupta (2018), Antonakakis et al.

(forthcoming), Çekin et al. (2019), Kang and Yoon (2019) and references cited therein), the objective of our paper is to forecast the EPUs of Brazil, China, India and Russia, i.e., the BRIC countries based on a vector autoregressive (VAR) framework (to accommodate for endogeneity) using information of EPUs of 18 other developed and developing economies. Further, we estimate the model using Bayesian approaches over the monthly period of March, 2003 to December, 2018, with the initial out-of-sample period starting in January, 2008, to control for over-parametrization, given that we use in total as many as 22 EPUs of various countries.[1]

Note that, the decision to use information only from the EPUs is an effort to produce forecasts of policy-related uncertainties in the BRICs independent of the current state of the economy, given that EPU is in fact considered to be a leading indicator of the economy. As far as our focus on the BRIC bloc is concerned, it emanates from the emergence of this group as a powerful economic force, already contributing to more than a quarter of global output, which in turn, is expected to surpass that of the G7 countries by 2050 (Plakandaras et al., 2019a). In addition, trade by these economies with the rest of the world has been growing at a fast rate, and based on the 2015 Global Energy Statistical Yearbook by Enerdata, the share of these countries in the total volume of world trade is about 18% (USD 7.7 trillion), which in fact is about 71% higher than what it was in 2008. Naturally, uncertainty in these key emerging markets is likely to contribute to global slowdown by prolonging the effects of increases in uncertainty in a particular country through feedbacks via the trade-channel (Balli et al., 2017). Hence, accurate prediction of EPU in this bloc is clearly of high importance considering the growth trends mentioned above.

To the best of our knowledge, this is the first paper to forecast EPU of the BRIC countries based on past information of policy-related uncertainty associated with this bloc and that of 18 other countries based on Bayesian VARs (BVARs). In the process, we aim to add, by looking at the issue of forecastability of EPU from the perspective of emerging markets, to the two studies of Wang et al. (2015) and Degiannakis and Filis (2019), which concentrated on developed

[1]Note that, due to the unavailability of monthly data on EPU, we were not able to include South Africa in to the analysis, and hence could not analyze the BRICS bloc as a whole.

economies of Europe and the US. The remainder of the paper is organized as follows: Section 2 describes the data and Bayesian methods applied on the VAR, Section 3 discusses the results, while Section 4 concludes.

2 Data and Methodologies

As indicated earlier, uncertainty is unobservable, and hence one requires ways to measure it. In this regard, besides the various alternative metrics of uncertainty associated with financial markets (such as the implied-volatility index (popularly called the VIX), realized volatility, idiosyncratic volatility of equity returns, corporate spreads), there are primarily three broad approaches to quantify uncertainty (Gupta et al., 2018): First, a news-based approach, where searches of major newspapers are conducted for terms related to economic and policy uncertainty, and then the results are used to construct indexes of uncertainty; Second, measures of uncertainty are derived from stochastic-volatility estimates of various types of small and large-scale structural models related to macroeconomics and finance, and; Third, uncertainty is obtained from dispersion of professional forecaster disagreements. As far as our metric of uncertainty is concerned for the BRIC bloc, we rely on measure derived from the news-based approach of Baker et al. (2016), i.e., EPU, primarily due to the fact that this measure does not require any complicated estimation of a large-scale model to generate it in the first place, and hence, is not model-specific. In addition, the data is available publicly for download for a large number (22) of developed and developing economies.[2]

Our data set includes the EPU indexes for a total of 22 countries that have data available at monthly frequency over the period of March, 2003 to December, 2018. These countries are Australia, Brazil, Canada, Chile, China, France, Germany, Greece, Hong Kong, India, Ireland, Italy, Japan, South Korea, Mexico, Netherlands, Russia, Singapore, Spain, Sweden, the United Kingdom (UK), and the US, among which Brazil, China, India, and Russia, i.e, the BRIC coun-

[2]These indexes can be downloaded from: https://www.policyuncertainty.com/.

tries are our primary interest. The start and end dates of our analysis are purely governed by the availability of data on the EPUs of the 22 countries at the time of writing this paper. The augmented Dickey-Fuller test (see Dickey and Fuller (1979, 1981)) shows that each of the 22 EPUs possesses a unit root, and hence we apply the log-difference transformation to the time series.[3] In other words, we work with the growth-rates of this measure of uncertainty, which in any event is the more relevant metric when it comes to relating it to economic activity, as changes in EPU tends to capture uncertainty shocks, as pointed out in the literature (cited in the introduction) associated with spillovers of uncertainty.

We consider two sets of VAR specifications, a small model with 4 BRIC EPUs as this bloc is our main focus, and a large model with all 22 EPUs, to see if the evidence in favor of spillover of EPUs across countries can be used to obtain forecasting gains for the EPUs of the BRIC. For each model, we follow Koop et al. (2019) and choose a relatively large lag length, $p = 13$.[4] Such high-dimensional VARs usually rely on Bayesian estimation methods and a technical difficulty exists due to the fact that a large number of parameters need to be estimated. There are two typical methods to overcome over-parametrization concerns, both involve the idea of "compression." The first method is to use prior shrinkage on the parameters. Examples include the Minnesota prior (see Doan et al. (1984)), the least absolute shrinkage and selection operator (or LASSO, see Park and Casella (2008)), and the stochastic search variable selection (or SSVS, see George et al. (2008)). The second method is to apply compression on the data instead of the parameters; see the Bayesian Compressed regression introduced by Guhaniyogi and Dunson (2015). In this regard, on one hand, Korobilis and Pettenuzzo (2019) propose the use of adaptive hierarchical priors, with the authors developing a simulation-free estimation algorithm that significantly saves computing time. This method involves a transformation on each single equation in the VAR that allows the joint posterior of the VAR coefficients to be approximated by the product of a number of scalar marginal posterior distributions. Within the

[3]Complete details of these results are available upon request from the authors.

[4]This choice is also in line with the fact that uncertainty has been shown to be a highly persistent process (Plakandaras et al., 2019b).

class of adaptive hierarchical priors, three special cases, namely the Normal-Jeffreys prior, the Normal-Gamma prior, and the Spike-and-Slab prior, are considered. On the other hand, Koop et al. (2019) introduce the Bayesian Compressed VAR. This method amounts to compressing a large number of variables via a randomly generated projection matrix so that the compressed data are much easier to work with. For complete details of these two methods, readers are referred to the two above-mentioned papers. Both methods are computationally simple and have been shown to outperform previously existing methods in terms of forecast accuracy.

We consider the following n-dimensional VAR(p) model,

$$\mathbf{y}_t = \mathbf{c} + \mathbf{A}_1 \mathbf{y}_{t-1} + ... + \mathbf{A}_p \mathbf{y}_{t-p} + \boldsymbol{\epsilon}_t, \tag{1}$$

where $\mathbf{y}_t$ is an $n \times 1$ vector of EPUs ($n = 4$ for the small model and $n = 22$ for the large model), $\mathbf{c}$ is an $n \times 1$ vector of constants, $\mathbf{A}_1, ..., \mathbf{A}_p$ are $n \times n$ matrices of coefficients, and $\boldsymbol{\epsilon}_t$ is an $n \times 1$ vector of error terms. We choose $p = 13$ as a relatively large lag length.

We utilize both methods developed by Korobilis and Pettenuzzo (2019) and Koop et al. (2019) to forecast EPUs of BRIC countries. Following their notations, we denote the three special adaptive hierarchical priors as N-J (Normal-Jeffreys), N-G (Normal-Gamma), and SNS (Spike-and-Slab), and the Bayesian compression method as BCVAR. As a benchmark, we consider the univariate AR(p) model.

We split the entire sample with T observations from March, 2003 to December, 2018 into two subsamples, one with the first T_0 observations for estimation and the other for forecast evaluation. The initial estimation sample spans over the March, 2003 to December, 2008 period, which is used to obtain initial parameter estimates and 1- to 12-month-ahead forecasts of EPUs. The in- and out-of-samples split is basically to forecast over the volatile periods of the world economy following the global financial crisis. We then use the recursive sampling method by adding one observation to the estimation sample at a time, re-estimating the model parameters, and re-forecasting the outcomes over the next 12 months. This exercise in such a recursive fashion gives a sequence of out-of-sample forecasts, $\widehat{\text{EPU}}_{i,t+h}$. For each of the forecasting methods considered in this paper, the out-of-sample forecast accuracy is assessed by the mean squared forecast error (MSFE), i.e.,

$$\text{MSFE}(i,h) = \frac{1}{T - T_0 - h + 1} \sum_{t=T_0}^{T-h} \left(\widehat{\text{EPU}}_{i,t+h} - \text{EPU}_{i,t+h} \right)^2, \tag{2}$$

where i denotes a country and h denotes the forecast horizon.

To evaluate the out-of-sample performance of each of the four recently developed forecasting methods (N-J, N-G, SNS, and BCVAR) relative to the benchmark AR model, we utilize the out-of-sample R^2_{OS} statistic of Campbell and Thompson (2007), i.e.,

$$R^2_{OS}(i,h) = 1 - \frac{\text{MSFE}(i,h)}{\text{MSFE}(i,h)_{AR}}, \tag{3}$$

where $\text{MSFE}(i,h)_{AR}$ is the mean squared forecast error computed from the benchmark AR(p) model. The R^2_{OS} statistic captures the proportional reduction in the MSFE of each forecasting method relative to the benchmark model and a positive value is an indicator of outperformance. The significance of the R^2_{OS} statistic is evaluated via a one-sided t-test. These results are presented in Tables 1 and 2.

3 Empirical Results

We now turn to our forecasting results. As indicated earlier, the small VAR includes EPUs of the 4 BRIC countries only, where the number of parameters to be estimated is relatively small. While all forecasting methods using the idea of compression significantly outperform the benchmark AR model for most of the BRIC EPUs at the majority of the forecast horizons, we do find in Table 1 that they also under-perform relative to the AR model occasionally. For example, the BCVAR increases the mean squared forecast error of the AR model by 18 percent for the 2-month-ahead forecast of China's EPU. The N-J method slightly under-performs the benchmark for the forecast of China's EPU at various horizons.

When EPUs of the other 18 countries are added into the model, the number of model parameters amplifies, and the idea of compression becomes important in this case. In general, consistent with the spillover literature, the inclusion of the EPUs from the other countries help in forecasting the EPUs for BRIC countries, especially for China and Brazil. This is easy to understand given the economic connectedness of these two countries with the rest of the world. Table 2 shows that the methods of compressing the parameters, i.e., N-J, N-G, and SNS, consistently outperform the benchmark AR model for all of the BRIC EPUs at each of the forecast horizons. While the improvement is usually not statistically significant at the very short horizon, these methods stand out at longer horizons. For example, the N-G and SNS methods significantly reduce the mean squared forecast error of the benchmark model by about 10-15 percent for all BRIC EPUs at 3- to 10-month-ahead horizons. The BCVAR, a method of compressing the data, performs as well as the N-G and SNS methods at longer horizons. However, at short horizons, it under-performs relative to the benchmark model for the EPUs of China and Russia.

In sum, in terms of forecasting the EPUs of BRIC countries is concerned, our empirical analysis suggests that incorporating information of EPUs of other developed and developing countries in the model matters in terms of forecasting gains, irrespective of whether we compress the parameters (i.e., via shrinkage priors) or the data.[5] But, when we compare across these two Bayesian approaches the former method performs relatively better than the latter, especially at shorter horizons. The fact that EPUs of other countries matter is more or less in line with the findings of Degiannakis and Filis (2019), who found that a global measure of EPU is the best predictor in forecasting the European EPU, which in turn, is an indication of spillovers of EPUs across economies, and they being connected to each other.

[5]We focus on these two methods recently developed by Korobilis and Pettenuzzo (2019) and Koop et al. (2019) as they have shown to be computationally simple and better than other methods in terms of the forecasting performance in a number of applications. Another simple and traditional method is to use Bayesian VARs with Minnesota priors. This method also works well for the forecast of BRIC EPUs, except at very short forecast horizons. Results are available upon request from the authors.

Table 1: Out-of-sample forecast R^2_{OS} statistics of the small VAR

Variable	Method	Forecast horizon 1	2	3	4	5	6	7	8	9	10	11	12
EPU_Brazil	N-J	8.019	9.338	8.773	9.226	5.712	4.936	5.205	5.324	4.604	3.693	4.123	5.435
		[0.162]	[0.034]	[0.023]	[0.025]	[0.115]	[0.134]	[0.134]	[0.128]	[0.198]	[0.248]	[0.21]	[0.132]
	N-G	4.437	11.94	15.493	13.97	13.935	14.822	12.114	10.403	8.973	8.43	6.495	6.037
		[0.354]	[0.073]	[0.009]	[0.021]	[0.015]	[0.009]	[0.037]	[0.055]	[0.109]	[0.126]	[0.201]	[0.185]
	SNS	10.272	13.487	13.31	13.912	13.857	14.723	12.26	10.845	9.077	8.414	6.703	6.38
		[0.144]	[0.029]	[0.016]	[0.016]	[0.011]	[0.006]	[0.028]	[0.04]	[0.096]	[0.118]	[0.186]	[0.166]
	BCVAR	5.244	12.065	14.204	10.627	11.532	11.986	11.233	9.443	6.993	5.808	4.631	6.08
		[0.286]	[0.041]	[0.006]	[0.033]	[0.016]	[0.014]	[0.028]	[0.047]	[0.133]	[0.177]	[0.243]	[0.165]
EPU_China	N-J	11.724	3.539	3.448	-3.561	-4.552	-4.789	-5.412	-3.382	-4.479	2.036	3.717	2.47
		[0.024]	[0.211]	[0.212]	[0.774]	[0.865]	[0.906]	[0.952]	[0.847]	[0.931]	[0.226]	[0.088]	[0.162]
	N-G	4.039	-3.236	5.366	9.062	11.072	14.072	11.702	12.553	10.214	10.952	13.644	9.706
		[0.303]	[0.703]	[0.131]	[0.039]	[0.006]	[0.002]	[0.005]	[0.003]	[0.008]	[0.007]	[0.003]	[0.008]
	SNS	8.814	4.07	7.226	5.965	8.278	10.538	8.947	10.514	8.438	9.938	12.429	8.898
		[0.08]	[0.187]	[0.054]	[0.117]	[0.022]	[0.007]	[0.011]	[0.005]	[0.015]	[0.007]	[0.003]	[0.009]
	BCVAR	-7.508	-18.385	-1.857	3.431	3.094	5.598	4.27	5.407	5.772	8.023	7.618	5.191
		[0.707]	[0.95]	[0.624]	[0.215]	[0.246]	[0.105]	[0.098]	[0.068]	[0.036]	[0.013]	[0.021]	[0.04]
EPU_India	N-J	5.274	13.969	10.222	13.083	13.667	9.561	6.875	8.385	10.301	12.176	6.035	5.678
		[0.256]	[0.031]	[0.069]	[0.028]	[0.018]	[0.029]	[0.088]	[0.043]	[0.01]	[0.002]	[0.037]	[0.006]
	N-G	8.402	8.444	9.713	11.581	12.322	11.867	11.41	10.953	11.603	11.518	4.016	3.528
		[0.066]	[0.038]	[0.016]	[0.005]	[0.003]	[0.004]	[0.006]	[0.001]	[0.001]	[0.001]	[0.06]	[0.071]
	SNS	7.994	9.814	8.51	11.9	12.036	11.298	10.468	10.355	11.527	11.88	4.656	3.961
		[0.077]	[0.025]	[0.042]	[0.005]	[0.005]	[0.004]	[0.009]	[0.002]	[0.001]	[0]	[0.037]	[0.049]
	BCVAR	8.361	11.764	16.141	11.582	12.817	7.476	7.099	7.775	7.908	9.335	3.277	3.257
		[0.145]	[0.032]	[0]	[0.004]	[0.001]	[0.028]	[0.029]	[0.004]	[0.006]	[0.001]	[0.083]	[0.082]
EPU_Russia	N-J	-4.574	6.389	8.483	5.168	3.033	4.682	4.379	4.473	0.217	2.163	2.284	4.873
		[0.699]	[0.07]	[0.027]	[0.124]	[0.21]	[0.103]	[0.08]	[0.106]	[0.469]	[0.191]	[0.178]	[0.011]
	N-G	-2.465	9.102	9.978	10.691	7.407	10.292	10.15	9.944	5.423	5.168	5.063	5.744
		[0.6]	[0.081]	[0.06]	[0.03]	[0.071]	[0.016]	[0.002]	[0.003]	[0.035]	[0.03]	[0.027]	[0.006]
	SNS	-2.104	9.668	9.929	11.297	8.584	10.545	10.409	10.265	5.252	4.7	4.787	5.706
		[0.59]	[0.053]	[0.043]	[0.011]	[0.024]	[0.008]	[0.001]	[0.002]	[0.037]	[0.041]	[0.032]	[0.006]
	BCVAR	-9.735	6.843	8.79	7.405	4.534	6.589	6.503	7.744	4.399	4.3	4.998	4.922
		[0.829]	[0.116]	[0.064]	[0.076]	[0.159]	[0.05]	[0.008]	[0.007]	[0.053]	[0.045]	[0.026]	[0.009]

The R^2_{OS} statistics (in percent) capture the proportional reduction in the mean squared forecast error of each forecasting method relative to the benchmark model. p-values are reported in brackets.

Table 2: Out-of-sample forecast R^2_{OS} statistics of the large VAR

		Forecast horizon											
Variable	Method	1	2	3	4	5	6	7	8	9	10	11	12
EPU_Brazil	N-J	8.529	7.863	6.179	7.104	7.341	8.281	9.491	8.956	6.82	5.769	4.634	6.192
		[0.16]	[0.077]	[0.096]	[0.083]	[0.077]	[0.046]	[0.039]	[0.04]	[0.121]	[0.156]	[0.216]	[0.127]
	N-G	5.891	9.581	14.685	15.584	14.146	15.259	12.001	10.447	8.825	8.347	6.474	6.046
		[0.308]	[0.13]	[0.013]	[0.012]	[0.014]	[0.008]	[0.038]	[0.055]	[0.112]	[0.129]	[0.202]	[0.185]
	SNS	9.753	12.671	12.852	13.653	14.044	14.89	12.669	11.055	9.145	8.523	6.635	6.314
		[0.159]	[0.041]	[0.018]	[0.019]	[0.011]	[0.007]	[0.025]	[0.039]	[0.097]	[0.116]	[0.189]	[0.169]
	BCVAR	7.23	12.947	19.014	13.156	15.152	15.752	13.164	11.721	9.906	7.981	6.983	6.777
		[0.257]	[0.05]	[0.002]	[0.034]	[0.012]	[0.009]	[0.028]	[0.032]	[0.092]	[0.145]	[0.183]	[0.172]
EPU_China	N-J	14.65	4.933	7.549	3.462	5.228	5.766	4.751	5.542	2.844	5.991	7.245	5.361
		[0.011]	[0.175]	[0.038]	[0.217]	[0.058]	[0.05]	[0.059]	[0.02]	[0.165]	[0.019]	[0.006]	[0.03]
	N-G	5.919	-2.314	4.134	8.417	11.212	13.951	11.652	12.482	10.062	10.956	13.661	9.654
		[0.214]	[0.649]	[0.208]	[0.057]	[0.006]	[0.002]	[0.005]	[0.003]	[0.008]	[0.007]	[0.003]	[0.008]
	SNS	10.523	6.358	8.687	8.153	10.336	11.628	9.72	11.186	8.686	9.844	12.491	8.809
		[0.043]	[0.095]	[0.033]	[0.059]	[0.009]	[0.005]	[0.009]	[0.004]	[0.014]	[0.008]	[0.003]	[0.01]
	BCVAR	-7.457	-22.613	-5.596	9.217	9.723	13.243	8.681	9.806	9.648	10.975	10.744	6.637
		[0.691]	[0.971]	[0.789]	[0.014]	[0.013]	[0.002]	[0.011]	[0.008]	[0.006]	[0.002]	[0.012]	[0.017]
EPU_India	N-J	13.791	11.979	9.637	10.938	11.77	10.091	8.979	8.631	9.158	10.129	3.922	4.163
		[0.011]	[0.006]	[0.008]	[0.001]	[0]	[0.001]	[0.006]	[0.002]	[0.002]	[0.001]	[0.039]	[0.025]
	N-G	6.495	7.518	9.425	11.976	12.307	11.744	11.344	10.887	11.57	11.513	4.016	3.581
		[0.136]	[0.068]	[0.02]	[0.004]	[0.003]	[0.004]	[0.005]	[0.001]	[0.001]	[0]	[0.06]	[0.069]
	SNS	7.671	8.264	6.823	10.658	10.988	10.97	10.749	10.231	11.051	11.189	4.203	3.774
		[0.079]	[0.042]	[0.073]	[0.006]	[0.005]	[0.004]	[0.006]	[0.002]	[0.001]	[0]	[0.043]	[0.05]
	BCVAR	5.145	6.943	12.355	9.836	14.062	10.79	7.02	7.844	9.49	9.928	3.616	3.303
		[0.282]	[0.191]	[0.012]	[0.016]	[0.001]	[0.008]	[0.07]	[0.018]	[0.007]	[0.003]	[0.062]	[0.072]
EPU_Russia	N-J	2.288	5.844	7.825	8.362	7.419	7.192	5.547	5.914	2.029	2.806	3.304	5.416
		[0.39]	[0.092]	[0.028]	[0.022]	[0.021]	[0.029]	[0.048]	[0.043]	[0.207]	[0.123]	[0.09]	[0.006]
	N-G	1.215	9.862	9.654	10.127	7.428	10.328	10.094	9.939	5.549	5.209	5.018	5.768
		[0.448]	[0.062]	[0.062]	[0.037]	[0.071]	[0.015]	[0.002]	[0.003]	[0.032]	[0.029]	[0.028]	[0.006]
	SNS	2.814	11.041	10.482	11.494	8.985	10.371	9.802	9.663	5.182	4.588	4.57	5.577
		[0.374]	[0.028]	[0.033]	[0.01]	[0.019]	[0.009]	[0.003]	[0.004]	[0.04]	[0.045]	[0.039]	[0.007]
	BCVAR	-13.233	8.685	10.925	6.462	3.947	7.755	7.111	9.305	4.81	3.949	5.468	5.183
		[0.882]	[0.103]	[0.048]	[0.137]	[0.231]	[0.053]	[0.017]	[0.004]	[0.062]	[0.099]	[0.024]	[0.018]

The R^2_{OS} statistics (in percent) capture the proportional reduction in the mean squared forecast error of each forecasting method relative to the benchmark model. p-values are reported in brackets.

4 Concluding Remarks

In this paper, we examine the forecastability of monthly news-based policy-related economic uncertainty (EPU) of the BRIC bloc using information of EPUs of 18 other developed and developing countries based on Bayesian VARs. In line with the recent evidence of interconnectedness of the EPUs across countries, we find that incorporating information of EPUs of the other countries in the model does produce higher forecasting gains relative to the models which either include own-lagged EPUs or lagged EPUs of the BRIC bloc. This result tends to hold, irrespective of whether the Bayesian approaches used compress the parameters the data to prevent the problem of over-parametrization in large-scale VARs. But when we compare across the two Bayesian approaches used, the shrinkage-priors imposed on the parameters tend to perform relatively better than the data compression method, especially at shorter horizons. Our results imply that, in the wake of spillovers, accurate forecasting of uncertainty of Brazil, Russia, India and China, and the appropriate design of policies thereafter, must account for not only past EPUs of its own, but also uncertainties of other economies both within and outside the BRIC bloc.

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