Is There a Role for Uncertainty in Forecasting Output Growth in OECD Countries? Evidence from a Time-Varying Parameter-Panel Vector Autoregressive Model[#]

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Abstract

This paper uses a time-varying parameter-panel vector autoregressive (TVP-PVAR) model to analyze the role played by domestic and US news-based measures of uncertainty in forecasting the growth of industrial production of twelve Organisation for Economic Co-operation and Development (OECD) countries. Based on a monthly out-of-sample period of 2009:06 to 2017:05, given an in-sample of 2003:03 to 2009:05, there are only 46 percent of cases where domestic uncertainty can improve the forecast of output growth relative to a baseline monetary TVP-PVAR model, which includes inflation, interest rate and nominal exchange rate growth, besides output growth. Moreover, including US uncertainty does not necessarily improve the forecasting performance of output growth from the TVP-PVAR model which includes only the domestic uncertainty along with the baseline variables. So, in general, while uncertainty is important in predicting the future path of output growth in the twelve advanced economies considered, a forecaster can do better in majority of the instances by just considering the information from standard macroeconomic variables.

Keywords: Economic Uncertainty, Output Growth, Time-Varying Parameter, Panel Vector Autoregressions, OECD Countries.

JEL Codes: C33, C53, E32, E37, E60.

[#] We would like to thank an anonymous referee for many helpful comments. However, any remaining errors are solely ours.
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1. Introduction

Following the "Great Recession" there has been a renewed interest in the link between uncertainty and the macroeconomy, using both theoretical and empirical approaches (see Gupta et al., (2018a, b) for detailed literature reviews in this regard). Overall, this line of research tends to overwhelmingly confirm the negative impact of uncertainty on economic activity. Interestingly, barring a few exceptions (Karnizova and Li, 2014; Balcilar et al., 2016; Junttila and Vataja, 2017; Pierdzioch and Gupta 2017; Segnon et al., 2018), empirical studies trying to recover the link between uncertainty and economic activity have been in-sample structural analyses, concentrating on the US, the UK or the aggregate Euro area.

Karnizova and Li (2014) use probit models to highlight the role of uncertainty in forecasting U.S. recessions, while Balcilar et al., (2016) emphasize the gains from using mixed-frequency Markov-switching models that includes uncertainty in forecasting U.S. recessions.[1] Junttila and Vataja (2017) show that inclusion of uncertainty for either the U.S., the UK, or the overall Euro area improves the forecasting ability of benchmark predictive regression models that contain standard financial market information, especially for the period before the 2008 global financial crisis. Unlike the above mentioned three studies, which concentrate on post-World War II data, Segnon et al., (2018) forecast quarterly U.S. GNP over the period from 1900 to 2014 using various linear and nonlinear bivariate models featuring uncertainty. They show that, while a Markov-switching time-varying parameter vector autoregressive (MS-TVP-VAR) model in most cases cannot be outperformed by its competitors when point forecasts are being studied, a Bayesian VAR (BVAR) model with stochastic volatility is the best-performing model in the majority of the cases for density forecasts. Finally, Gupta and Pierdzioch (2017) use a Boosted Regression Trees (BRT) approach to study the potentially nonlinear link between various standard predictors, components of uncertainty, and U.S recessions over the monthly period of 1889 to 2016. An analysis based on receiver-operating-characteristic (ROC) curves showed that including war-related uncertainty in the list of predictors improves out-of-sample forecasting performance at a longer-term forecasting horizon; however, the predictive value of this component relative to other components of uncertainty is found to have declined in the second half of the 20th century. In general, the above-mentioned time-series based country-specific studies dealing with forecasting exercises, does suggest that uncertainty contains useful information in predicting economic activities over out-of-sample periods.

There is a widely held view that the importance of variables and models should be judged based on out-of-sample validations (Campbell, 2008). Given this line of thinking, and against this backdrop of (limited) evidence on the out-of-sample forecasting performance of uncertainty with respect to subsequent developments of economic activity only restricted to the aggregate Euro area, besides the US and the UK, we, in this paper for the first-time, use a Time Varying Parameter-Panel Vector Autoregressive (TVP-PVAR) model (Koop and Korobilis, forthcoming) to analyze the ability of uncertainty to forecast movements of output in twelve Organisation for Economic Co-operation and Development (OECD) countries (Australia, Canada, France, Germany, Ireland, Italy, Japan, South Korea, the Netherlands, Spain, Sweden, and the UK). Note that, the US is left out, since we not only analyze the impact of the domestic uncertainty of these economies, but also the possible role played by the uncertainty of the US economy (Colombo, 2013; Jones and Olson, 2015), given its dominance in the world economic structure, on the growth of these twelve OECD countries. In an increasingly globalized world, where macroeconomic events in one country can spillover to another country, the need for models which accommodate such interlinkages is, understandably, an obvious choice over time-series approaches, with the need being fulfilled by a PVAR framework which

[1] Balcilar et al., (2017) use bivariate long-memory models to show that uncertainty can also forecast U.S. inflation in an effective manner compared to short-memory models.

jointly models many macroeconomic variables in many countries.[2] The TVP-PVAR, being a time-varying approach based on Dynamic Model Averaging (DMA) and Dynamic Model Selection (DMS), controls for the nonlinear relationship between uncertainty and economic activity (Balcilar et al., 2016; Pierdzioch and Gupta, 2017), but also allows for heterogeneous coefficients (slopes or responses) across the equations of each of the cross-sectional units, i.e., the twelve countries.

Time-varying parameters also allows us to consider various sources of uncertainty that pertain to panel VARs, by using a Bayesian dynamic learning prior that allows us to learn interesting model features from the data. The Bayesian learning procedure is dynamic, suggesting that at each point in time a different model structure might hold. In addition, there is a great deal of evidence that stochastic volatility is extremely important for forecasting, but there is mixed evidence about whether allowing for time-varying intercepts and autoregressive coefficients is important. The TVP-PVAR specification that we use nests models with faster or slower drifts in coefficients, as well as a fully time-invariant PVAR structure. Thus we can estimate in a time-varying manner the amount of time variation in the error covariance and VAR coefficients. Finally, the TVP-PVAR accounts for uncertainty about the size of the panel VAR. The learning mechanism on which the TVP-PVAR model is based looks at the most recent out-of-sample performance at each point in time and then shrinks the PVAR model to an optimal parsimonious structure. Indeed, one could use Bayesian multi-country VARs, Global VARs, multi-country factor models, and spatial VARs as well, but then the flexible learning procedure used in the TVP-PVAR, which acts as a safeguard against overfitting and poor forecasting performance, is not accounted for by these alternative modelling approaches.

The remainder of the paper is organized as follows: Section 2 presents the methodology, while Section 3 discusses the data and results, with Section 4 concluding the paper.

2. Methodology

Recently, Koop and Korobilis (forthcoming) developed econometric methods for estimating large Bayesian time-varying parameter panel vector autoregressions (TVP-PVARs) with time-varying error covariances. Large TVP-PVARs contain huge numbers of parameters which can lead to over-parameterization and computational concerns. To address this issue, the authors use hierarchical priors which reduce the dimension of the parameter vector and allow for dynamic model averaging or selection over TVP-PVARs of different dimension and different priors. Finally, Koop and Korobilis (forthcoming) use forgetting factor methods which greatly reduce the computational burden.

Following the notation of Koop and Korobilis (forthcoming), we denote $Y_t = (y'_{1t}, y'_{2t}, \dots, y'_{Nt})$ for t=1,…,T is the $NG \times 1$ vector of dependent variables where y'_{it} is the $NG \times 1$ vector of dependent (macroeconomic) variables of the cross-sectional unit (country, in our case) *i*, *i*=1,…,*N*. The *i*-th equation of the PVAR with *p* lags takes the form:

$$y_t = A_i^1 Y_{t-1} + \cdots + A_i^p Y_{t-p} + u_{it}, \tag{1}$$

where A_i^j for *j*=1,…,*p* are $G \times NG$ matrices PVAR coefficients for the country unit *i*. Also u_{it} is a $NG \times 1$ vector of disturbances, uncorrelated over time, where $u_{it} \sim N(0, \sum_{ii})$. The error between

[2] Given that in a PVAR model, each of the countries should have the same number of variables in the equations, it would result in an unbalanced model if the US is included in the analysis when we are comparing the possible additional predictive power emanating from the US uncertainty measure, over and above the domestic meric of the same.

countries may be correlated and we define $E(u_{it}u_{jt})y_t = \sum_{ij}$ and $\sum$ to be the entire $NG \times NG$ error covariance matrix for $u_t = (u_{it,\dots,}u_{Nt}).'$ Let $A^j = (A_1^j, \dots, A_N^j)$ for j=1,…,p and $\alpha = (vec(A^1)', \dots, vec(A^p)')'$. The TVP-PVARs model allows the coefficients in the PVAR to be time varying, therefore all coefficients in Eq(1) have t subscripts such that $\alpha = (vec(A_t^1)', \dots, vec(A_t^p)')'$ is the $K \times 1$ vector storing all PVAR parameters at time t. The TVP-PVAR model in matrix form can be written as:

$$Y_t = X_t'\alpha_t + u_t, \tag{2}$$

where $X_t = I \otimes (Y_{t-1}', \dots, Y_{t-p}')'$, and $u_{it} \sim N(0, \sum_t)$. In order to reduce the dimension of the TVP-VAR, we use DMA methods as described in Koop and Korobilis (forthcoming) by using the following hierarchical prior:

$$\alpha_t = \Xi\theta_t + e_t$$
$$\theta_t = \theta_{t-1} + \omega_t,$$

$\alpha_t$is the factor structure for the TVP-VAR coefficients, and $\Xi = (\Xi_{1,\dots,}\Xi_q)$ are known materics. θ_t is an $K \times 1$ vector of unknown parameters, and $\omega_t \sim N(0, W_t)$ where W_t is an$R \times R$ covariance matrix.[3]

3. Data and Results

In our case, the model has N countries = 12, and G variables for each country, with the baseline model having output growth, inflation, short-term interest rate and nominal exchange rate growth, to which we add the domestic uncertainty variable, and then the uncertainty variable of the US economy. Hence, G ranges from 4 to 6, with the baseline 4-variable model being the standard open economy monetary VAR model. Based on data availability to produce a balanced panel, the countries included are Australia, Canada, France, Germany, Ireland, Italy, Japan, South Korea, the Netherlands, Spain, Sweden, and the United Kingdom (UK), covering the monthly period of 2003:03 to 2017:05.

Output growth is measured by month-on-month industrial production growth, whereas month-on-month inflation is derived from the consumer price index, and we also use the month-on-month growth rate of the dollar-based nominal exchange rate to capture movements in the currency market. Data on these three variables comes from the Main Economic Indicators (MEI) Database of the OECD countries.[4] Barring the Euro area countries (France, Germany, Ireland, Italy, the Netherlands, and Spain), Japan, and the United Kingdom, the short-term interest rate data is derived from OECD's MEI Database for Australia, Canada, South Korea and Sweden. The common short-term interest rate of the Euro area countries, and the individual interest rates of Japan and the UK corresponds to the Shadow Short Rates (SSR) developed by Krippner (2013) based on models of term-structure and is available for download from the website of the Reserve Bank of New Zealand.[5] We use the SSR, instead of the standard short-term interest rates for these eight economies, due to the zero lower bound scenario faced by these countries during and post the Great Recession.[6]

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[3] Please refer to Koop and Korobilis (2015) for detailed description on the estimation and forecasting of TVP-PVAR and DMA.

[4] The data is available for download at: http://www.oecd.org/sdd/oecdmaineconomicindicatorsmei.htm.

[5] The data can be downloaded from the following link: https://www.rbnz.govt.nz/research-and-publications/research-programme/additional-research/measures-of-the-stance-of-united-states-monetary-policy/comparison-of-international-monetary-policy-measures.

[6] The yield curve-based framework developed by Krippner (2013) essentially removes the effect that the option to invest in physical currency (at an interest rate of zero) has on yield curves, resulting in a hypothetical "shadow yield curve" that would exist if physical currency were not available. The process allows one to answer the question: "what

Uncertainty is a latent variable, and hence measuring the same is not straight-forward, with many existing approaches (see, Strobel (2015) for a detailed discussion in this regard). However, in line with the above-mentioned studies that have analyzed the forecasting ability of uncertainty for economic activity, and also due to data availability for the multiple countries used in this paper, we rely on the news-based measure of Economic Policy Uncertainty (EPU) index to capture uncertainty. The data on the EPU indices for the twelve countries is based on the work of Baker et al., (2016).[7] These authors construct indices for major economies of the world by quantifying month-by-month searches for newspaper coverage on terms related to policy-related economic uncertainty. For inclusion in the index, the articles must contain all of the three terms of economy, policy and uncertainty simultaneously. The EPU index is converted into its natural logarithmic form.

We now turn to the results from the model estimated with a lag-length (p) set at 1, based on the Schwarz Information Criterion (SIC), and an out-of-sample period covering 2009:06 to 2017:05, with 2003:03 to 2009:05 as the in-sample. Our models are estimated in a recursive fashion (i.e., expanding window) over the out-of-sample period to mimic the situation faced by a forecaster in reality. Since we use the latest available data vintage, and not real time data, our analysis can be dubbed a pseudo out-of-sample forecasting exercise. Note that with one lag, and one observation lost due to data transformation, our effective in-sample starts from 2003:05. This split, allows us to have enough observations for the in-sample estimation to obtain consistent estimators, but is also in line with the periods of global turmoil due to the Great Recession and the European sovereign debt crisis, with the peak in the domestic EPUs for all of the twelve economies falling in the out-of-sample period.

Table 1 shows the out-of-sample forecasting results for the industrial production growth of the twelve economies over the out-of-sample period for the horizons of one-, three-, six-, and twelve-month-ahead. The entries in Panel A of Table 1 correspond to the ratio of the Mean Square Forecast Error (MSFE) from the TVP-PVAR model with the individual country EPUs included in the model, relative to the baseline version of the same, which includes the output growth, inflation, short-term interest rate and the growth rate of the exchange rate. Understandably, if this ratio is less than one, then the MSFE from the model with EPU is lower than the MSFE of the baseline model, and hence, EPU produces forecasting gains for economic growth in the twelve economies considered here. As can be seen from the results, forecasting gains are observed for Australia at horizons 1, 3, and 6, for Canada and the Netherlands at one-month-ahead, for France at horizons 6 and 12, for Germany for all horizons barring twelve-month-ahead, for Ireland at all the four horizons considered, for Italy at horizons 1, 3 and 12, for Japan, Spain and Sweden at six-month-ahead only, for South Korea at all horizons barring one-month ahead. The only exception is the UK, for which, unlike in Junttila and Vataja (2017), we do not observe any forecasting gains emanating from the domestic EPU, though similar performance to the baseline model is observed at the horizons of six- and twelve-month-ahead.

In panel B of Table 1, we compare the relative MSFEs of the TVP-PVAR model which includes both domestic and US EPUs with the baseline model discussed above. As can be seen, forecasting gains are observed for Australia and Sweden at the one-year-ahead horizon, for Canada at horizons 1 and 3, for France and the Netherlands at horizons 6 and 12, for all the four horizons of Germany, for Ireland at horizons 9 and 12, for Italy at the shortest and the longest horizons, for Japan at horizons 3 and 6, for South Korea all the horizons barring the shortest one, and for Spain at horizon 6. However, comparing across Panels A and B of Table 1, when we look at cases where the TVP-

policy rate would generate the observed yield curve if the policy rate could be taken negative?" The "shadow policy rate" generated in this manner, therefore, provides a measure of the monetary policy stance after the actual policy rate reaches zero.

[7] The data can be downloaded from: www.policyuncertainty.com.

Table 1: Mean Square Forecast Errors (MSFEs) for Growth of Industrial Production from TVP-PVAR Model Relative to the Baseline

Panel A: Baseline Model with Domestic EPU

Horizon	Australia	Canada	France	Germany	Ireland	Italy	Japan	South Korea	The Netherlands	Spain	Sweden	UK
1	**0.992**$^{\#}$	**0.974***	1.022	**0.972***	**0.991**$^{\#}$	**0.994**	1.002	1.012	**0.995**	1.016	1.006	1.012
3	**0.985**$^{\#}$	1.000	1.006	**0.985**$^{\#}$	**0.997**	**0.983***	1.003	**0.993**	1.020	1.038	1.011	1.014
6	1.015	1.029	**0.970***	**0.984**$^{\#}$	**0.993**	1.006	**0.997**	**0.978***	1.002	**0.978***	**0.995**	1.000
12	**0.977***	1.000	**0.994**	1.018	**0.997**	**0.987**$^{\#}$	1.020	**0.993**	1.007	1.031	1.012	1.000

Panel B: Baseline Model with Domestic EPU and US EPU

Horizon	Australia	Canada	France	Germany	Ireland	Italy	Japan	South Korea	The Netherlands	Spain	Sweden	UK
1	1.008	**0.974***	1.022	**0.989**$^{\#}$	1.016	**0.994**	1.008	1.004	1.011	1.033	1.009	1.000
3	1.000	**0.991**$^{\#}$	1.012	**0.990**$^{\#}$	1.009	1.006	**0.987**$^{\#}$	**0.989**$^{\#}$	1.015	1.053	1.014	1.000
6	1.015	1.010	**0.988**$^{\#}$	**0.989**$^{\#}$	**0.993**	1.000	**0.988**$^{\#}$	**0.989**$^{\#}$	**0.974***	**0.957**$^{+}$	1.000	1.014
12	**0.977***	1.000	**0.994**	**0.988**$^{\#}$	**0.980***	**0.994**	1.033	**0.979***	**0.991**$^{\#}$	1.031	**0.990**$^{\#}$	1.000

Note: Entries in bold correspond to cases where the TVP-PVAR with measures of uncertainty outperforms the baseline model, as the relative MSFEs are less than one; #, *, and + correspond to the significant *MSE-F* test statistic at the 10 percent, 5 percent, and 1 percent levels of significance, respectively.

PVAR with domestic EPU performs better than the baseline, there are 12 cases[8] where the TVP-PVAR model with both domestic and US EPUs perform better than the model with the baseline variables plus the domestic EPU, with 3 cases[9] of equal performance. Interestingly, there are 13 scenarios[10] in which the TVP-PVAR model with domestic EPU only is outperforming the baseline model, as well as the TVP-PVAR model with both domestic and US EPU. Next, we analyzed the cases where we observe superior forecasting performances of the models with EPU (domestic, and domestic+US) relative to the benchmark, using the *MSE-F* test of McCracken (2007), which in turn is designed for nested models.[11] We find that in case of the model including domestic EPU, there are 13 cases which produces statistically significant gains (at least at the 10 percent level of significance) relative to the baseline, while this number increase to 18, when we have both domestic and US EPUs in the model. So including the US EPU over and above the domestic EPU does tend to provide some marginal statistical gain.

So from an overall perspective, out of the 48 cases considered, adding domestic EPU to the baseline model improves forecasting performances in 22 cases only, i.e., in 45.83 percent of the cases. Also, the US EPU does not necessarily improve the forecasting performance of output growth from the TVP-PVAR model with only the domestic EPU included along with the baseline variables.

In Table A1 in the Appendix of the paper, we report the density forecast results, which is essentially, sum of log predictive likelihood of the models with EPU (domestic, and domestic plus the US) included minus the sum of log predictive likelihood obtained for the benchmark model.[12] As can be seen, there is some improvement (i.e., 5 additional cases) in the case of the model with domestic EPU only, when we compare the point and density forecast results. In general, our conclusions drawn above from point forecasts remain robust when we look at density forecasts, especially for the model involving both domestic and US EPUs.[13]

4. Conclusion

In this paper we use a time-varying parameter-panel vector autoregressive (TVP-PVAR) model to analyze the role played by domestic and US news-based measures of uncertainty in forecasting the growth of industrial production of twelve (Australia, Canada, France, Germany, Ireland, Italy, Japan, South Korea, the Netherlands, Spain, Sweden, and the UK) Organisation for Economic Co-operation and Development (OECD) countries. Based on a monthly out-of-sample period of 2009:06 to 2017:05, given an in-sample of 2003:03 to 2009:05, we found out that barring the case of UK, there was at least one forecasting horizon of the four (one-, three-, six-, and twelve-month-

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[8] Canada at horizon 1, Germany, Ireland and Sweden at horizon 12, Italy at horizon 1, Japan at horizons 3 and 6, South Korea at horizons 3 and 12, the Netherlands at horizons 9 and 12 and Spain at horizon 9.

[9] At horizon 12 for Australia and France, and for the six-month-ahead forecast of Ireland.

[10] Australia and Ireland at horizons 1 and 3, France at horizon 6, Germany at all horizons barring the longest one, Italy at horizons 3 and 12, South Korea at horizon 6, the Netherlands at horizon 1 and Sweden at horizon 3.

[11] Formally, the *MSE-F* test statistic is equal to: $(T\text{-}R\text{-}h+1)\times(MSFE_0/MSFE_1\text{-}1)$, where $MSFE_0$ ($MSFE_1$) is the *MSFE* from the restricted (unrestricted) model, T is the total sample size, R is number of observations used for estimation of the model from which the first forecast is formed (i.e. the in-sample portion of the total number of observations), and h the forecasting horizon.

[12] We would like to thank an anonymous referee for the suggestion to conduct density forecasts.

[13] Based on the suggestion of an anonymous referee, we conducted an analysis where we included the US in our PVAR model, with the data sources being the same as for the other OECD countries which we described in the data segment of the paper. However note, in this case, we had to leave out the dollar-based exchange rate from our baseline model for obvious reasons, i.e., the equations of the PVAR need to have the same variables across the countries. Using this model, we found that in 27 out of the 52 cases under point forecasts, and 29 out of 52 cases under the density forecasts, the models with EPU outperformed the benchmark model. Complete details of these results are available upon request from the authors.

ahead) considered for which domestic uncertainty added value to forecasting growth of industrial production, over and above the information contained in standard predictors (inflation rate, interest rate, and growth of nominal exchange rate). But at the same time, these were only 46 percent of cases relative to the baseline monetary TVP-PVAR model. This number slightly improves when we analyze density forecasts. We not only analyze the impact of the domestic uncertainty of these economies, but also the possible role played by the uncertainty of the US economy, given its dominance in the world economic structure, on the growth of these twelve OECD countries. But, including US uncertainty does not necessarily improve the forecasting performance of output growth from the TVP-PVAR model which includes only the domestic uncertainty along with the baseline variables. So, in general, while uncertainty is important at times in predicting the future path of output growth in the twelve advanced economies considered, a forecaster can do better in majority of the instances by just considering the information from standard macroeconomic variables. In light of these (somewhat mixed) results, it would be interesting to extend our analysis to emerging markets, where the role of uncertainty in driving the economy could be possibly larger (due to their inherent volatile environment), over and above the information conveyed by the standard predictors. Also, to ensure that our weak results are not driven by the news-based measure of uncertainty, it would be interesting to first create a more economy-wide measure of the same using a structural (Factor-Augmented VAR) approach as in Jurado et al., (2015), and then reconduct our analyses. Having said this, it must be noted that the decision to use the EPU as a measure of uncertainty is due to the uniformity in the information content in the variables, as it is based on searches of leading newspapers of these countries for the three terms of economy, policy and uncertainty. The homogeneity of information might not be feasible when we use the approach of Jurado et al., (2015), as it might not be possible to get same number of comparable variables across the countries. Besides the EPU measure is also a real-time metric of uncertainty based on the news of a specific month and hence, does not suffer from the look-ahead bias we need to avoid in a forecasting exercise.

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APPENDIX

Table A1: Sum of log predictive likelihood for Growth of Industrial Production from TVP-PVAR Model Relative to the Baseline

Panel A: Baseline Model with Domestic EPU

Horizon	Australia	Canada	France	Germany	Ireland	Italy	Japan	South Korea	The Netherlands	Spain	Sweden	UK
1	-0.213	**1.267**	-0.885	**1.106**	-1.275	**0.007**	**1.025**	-1.048	**0.411**	-0.513	**0.240**	-0.235
3	**0.753**	-0.499	-0.721	**0.805**	**0.616**	**0.533**	**2.684**	**0.027**	-1.072	-0.083	**0.819**	-1.137
6	-1.229	-1.795	**1.193**	**0.371**	**2.311**	-0.372	**1.290**	**0.543**	**0.179**	**0.800**	**0.937**	-1.005
12	**1.498**	**0.67**2	**0.179**	-0.248	**1.478**	**1.146**	-1.241	-0.127	-0.310	-0.316	**0.507**	-0.102

Panel B: Baseline Model with Domestic EPU and US EPU

Horizon	Australia	Canada	France	Germany	Ireland	Italy	Japan	South Korea	The Netherlands	Spain	Sweden	UK
1	-0.815	**0.823**	-0.828	**0.373**	-3.111	-0.627	-0.257	-0.774	-0.704	-0.710	**0.528**	-0.040
3	-0.267	-0.127	-1.086	**0.120**	-1.163	**0.210**	**3.232**	**0.322**	-0.201	-1.125	-0.828	-0.211
6	-1.013	-0.568	**1.195**	-0.206	**1.081**	**0.325**	**1.498**	**0.428**	**0.759**	**1.225**	**0.469**	-2.675
12	**0.668**	**1.066**	**0.102**	**0.243**	**3.489**	**0.533**	-0.952	0.573	-0.635	-0.628	**1.388**	-0.378

Note: Entries in bold correspond to cases where the TVP-PVAR with measures of uncertainty outperforms the baseline model, as the differences between the sum of log predictive likelihood of the models with EPUs relative to the baseline model are positive.