Point and Density Forecasting of Macroeconomic and Financial Uncertainties of the United States

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Abstract

We forecast macroeconomic and financial uncertainties of the US over the period of 1960:Q3 to 2018:Q4, based on a large data set of 303 predictors using a wide array of constant parameter and time varying models. We find that uncertainty is indeed forecastable, but while accurate point forecasts can be achieved without incorporating time-variation in the parameters of the small-scale models for macroeconomic uncertainty and large-scale models for financial uncertainty, it is indeed a requirement, along with a large data set, when producing precise density forecasts for both types of uncertainties.

Keywords: Macroeconomic and financial uncertainties, large number of predictors, constant parameter and time-varying models, forecasting

JEL Codes: C22, C53, C55

1. Introduction

Following the "Great Moderation", the world economy experienced a substantial increase in financial and macroeconomic volatility as a result of the global financial crisis starting in the summer of 2007, followed by a major global recession (i.e., the "Great Recession") between 2008 and 2009, and regional crises such as the sovereign debt crisis in Europe starting in 2010. As a result, the analysis of the role of volatility and uncertainty in the macroeconomy has regained a prominent role in recent years (see, Bloom (2014), Chuliá et al., (2017), and Gupta et al., (2020) for detailed reviews of this literature), with majority these studies concluding that unexpected large changes in uncertainty (or the closely related concepts of risk and volatility) represent an important source of macroeconomic and financial market fluctuations by causing delays in investment and hiring decisions of firms, and through the postponement of consumption spending by households in favor of precautionary savings (Bloom, 2009). While in general, uncertainty was considered to be reflecting exogenous factors such as natural disasters or geopolitical turmoil, a growing consensus is that uncertainty actually arises as an endogenous response to other macroeconomic forces, thus contributing to amplify their effects (Ludvigson et al., forthcoming).

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Given this, a pertinent question for policymakers is to determine the possible factors that can drive uncertainty, since forecasting the path of uncertainty, would allow policy authorities to determine in which direction the macroeconomy and financial markets are headed, and accordingly decide on the appropriate policy response. However, despite the importance of the issue of accurately forecasting uncertainty, to the best of our knowledge this literature is restricted to only three papers namely, Wang et al., (2015), Degiannakis and Filis (2019), and Gupta and Sun (2020). In the first paper, the authors successfully forecasted uncertainty 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 uncertainty in Europe, and showed that global uncertainty 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. The final study utilizes Bayesian methods to forecast uncertainty of Brazil, China, India and Russia (BRIC) based on uncertainties of additional 18 other developed and developing countries, and showed that incorporating information of uncertainties of other countries does indeed produce gains in forecasting the uncertainty of the BRIC bloc.

Against this backdrop, the objective of our paper is to add to this limited literature on predicting the future path of uncertainty, by forecasting macroeconomic and financial uncertainties of the US over the period of 1960:Q3 to 2018:Q4, based on a large data set of 303 predictors that covers the various sectors of the economy along with foreign influence and commodity prices, using a wide array of constant parameter and time varying models, and methods of shrinkages that have been recently developed to handle large datasets. A massive number of predictors, allow us to capture the various shocks namely, aggregate demand, aggregate supply, and policy-related shocks that are likely to drive uncertainty (Mumtaz and Musso, 2019), and hence rules out the possibility of omitted variable bias. At the same time, the underlying evolving relationship of uncertainty with its predictors (Hailemariam et al., 2019), is captured by the time-varying methods employed in the paper. Note that, if uncertainty is indeed predictable, i.e., our models with predictors perform better than a benchmark autoregressive model (which is without any independent variables), it would imply that uncertainty is in fact endogenous, as it is affected by economic conditions. This would be an important finding from the perspective of how an uncertainty shock is actually identified in structural macroeconometric models, for analysing its impact on macroeconomic and financial variables. Specifically speaking, if uncertainty is actually a forecastable variable, then it cannot be treated as exogenous for structural analysis (which is often the case (Gupta et al., (2019)), for example, while obtaining impulse response function of economic variables, following a shock to uncertainty. In other words, while accurate forecasting of uncertainty is important for policymakers, the predictability of the same has important implication for structural modelling.

To the best of our knowledge, this is the first attempt to forecast macroeconomic and financial uncertainties of the US using large number of predictors and econometric models. In addition, we not only provide point, but also density forecast of macroeconomic and financial uncertainties. The point forecast measures the central tendency of the target variable, or the best forecast. However, because this is an estimate, there is uncertainty around it. Hence, quantifying this uncertainty is important to capture how "sure" the researcher is regarding the precision of the forecasted value. One way to report the degree of sureness around point forecasts of macroeconomic and financial uncertainties is to use density forecasts. Density forecasts summarize the information regarding the estimated forecast distribution (quantiles), and have become very important for central banks and policy institutions to estimate and report the degree of uncertainty around their forecasts, while making policy decisions (Rossi, 2014). The remainder of the paper is organized as follows: Section 2 outlines the basics of the alternative models, while section 3 presents the data and forecasting results, with Section 4 concluding the paper.

2. Methodology

Our interest is to test if large set of predictors can help predict macroeconomic and financial uncertainties more accurately than small set of predictors as well as the benchmark model without predictors. Thus, we adopt thirteen alternative models including those proposed by Koop and Korobilis (2020), to forecast macroeconomic and financial uncertainties. These include Autoregressive – AR; Time varying Autoregressive – TVPAR; naïve principal component - FAC5; Partial Least Squares [PLS] regression; AR augmented with principal components (stochastic search variable selection (SSVS)/ FAC60) as outlined in George and McCulloch (1993); Bagging Algorithm - BAG (Breiman, 1996); Elastic Net Algorithm - ELN1 and ELN2 (Zou and Hastie, 2005); Gaussian Process Regression - GPR, Dynamic Model Averaging - DMA (Koop and Korobilis, 2012); and Variational Bayesian Dynamic Variable Selection - VBDVS1, VBDVS2 and VBDVS3 (Koop and Korobilis, 2020). These models are distinguished by constituent predictors, assumption of time dependence for the coefficients of incorporated exogenous predictors and parameter estimation method. Consequently, there are four sub-categorizations of the thirteen contending models by the constituent predictors: (i) models with no exogenous predictors (AR and TVPAR); (ii) factor models that incorporate the first five principal component factors as exogenous predictors (FAC5, BAG, GPR, DMA and VBDVS1); (iii) models incorporating the first sixty principal component factors as exogenous predictors (SSVS, ELN1 and VBDVS2); and (iv) models that incorporate all the plausible macro and financial variables (ELN2, PLS and VBDVS3). The last three model subgroups contain frameworks that are well suited to accommodate larger number of predictors and time period in comparison with other conventional methods. The predictive model is specified in the form defined by equation (1) as follows:

$$y_{t+h} = \alpha_t + \phi_{1,t} y_t + \phi_{2,t} y_{t-1} + x_t \beta_t + \varepsilon_{t+h} \qquad [1]$$

where y_{t+h} denotes $h-step$ ahead for the uncertainty measures [Macroeconomic or Financial Uncertainty]; x_t represents plausible exogenous predictor variables; α_t, $\phi_{1,t}$, $\phi_{2,t}$ and β_t are the model parameters corresponding respectively to the time varying intercept, coefficients of the first four lags of the uncertainty measure (as chosen by the Schwarz Information Criterion (SIC)) and exogenous predictors; while ε_{t+h} is the $h-step$ ahead disturbance term.

We briefly describe each of the competing models. In tandem with conventional practice, we consider the AR model with four lags as our benchmark model and estimate the model using the conventional ordinary least squares [OLS] regression. Another variant of the AR model that incorporates the assumption of time-dependent parameters – the time varying parameter AR [TVPAR] model is also considered as one of the candidate models and estimated using the Markov Chain Monte Carlo [MCMC] algorithm. FAC5 and BAG augment the AR model by incorporating the first five principal component factors; and are respectively estimated with OLS and as constant parameter regression using the bagging algorithm. The other two 5-factor models (DMA and VBDVS1), in addition to augmenting the conventional AR model, allow for the coefficients of the exogenous predictors to vary with time. The last 5-factor model – GPR is a non-parametric method that provides insight as to the appropriateness of forecasting the uncertainty of interest using either the time varying parameters or more complex non-linear functional forms. On the model subgroup with 60 factors as exogenous predictors: SSVS is estimated using SSVS prior with MCMC; ELN1 is estimated as constant parameter regression with the Elastic Net Algorithm; while VBDVS2 is estimated as TVP regression using dynamic variable selection with variational Bayes algorithm. On the last model subgroup that incorporates all the variables, another candidate model is considered – PLS, which is a more realistic principal component factor variant that takes cognizance of the predicted rather than the predictors only. While ELN and VBDVS variants are also candidate models in this subgroup given that they are well suited for high-dimensional data, with DMA, GPR and BAG shown in the extant literature to be unable to scale up to higher dimensions, be overparameterized and unstable, respectively.

On the forecast evaluation, we split and consider only 50% of the full data sample and subsequently obtain 1-, 2-, 4- and 8-quarters ahead out-of-sample forecasts. The predictive performance of the models are examined relative to the benchmark AR model using both point and density forecast evaluations tools – root mean square forecast error – RMSFE and average logarithm of predictive likelihoods – ALPL. The former takes the root of the mean of the squared difference between the actual and forecasted uncertainty data, while the latter is the average of the logged predictive likelihood (Bauwens et al., 2015). RMSFE and ALPL values are reported for the AR model, whereas in the case of the alternative models, their values relative to that of the benchmark model are reported. Consequently, RMSFE value that is less than one is considered to indicate support for the competing model over the benchmark, while value above one implies that the benchmark model performs better. Also, the smaller the value, the better the forecast of a specific model in comparison with other models. In the case of ALPL, values are expected to be positive to depict superior performance of the competing model than the benchmark, and larger for preference among the alternative models. Both forecast performance tools are employed to examine the specified out-of-sample forecasts.

3. Data and Results

3.1. Data

One must realize that uncertainty is a latent variable, and hence, it must be derived or estimated. There are multiple ways that have been recently proposed in the literature on uncertainty to measure it (see Gupta et al., (2018) for a detailed review in this regard). In this paper, we use the macroeconomic uncertainty (MU) and financial uncertainty (FU) measures of Jurado et al., (2015) and Ludvigson et al., (forthcoming), which in turn is the average time-varying variance in the unpredictable component of 134 macroeconomic and 148 financial time-series respectively, i.e., it attempts to capture the average volatility in the shocks to the factors that summarize real and financial conditions.[1] Unlike existing alternative measures of uncertainty, based on newspaper (text-based) approaches or volatility of a specific financial market, the metrics that we use are broadest measures of macroeconomic and financial uncertainties available for the US. The uncertainty indices are monthly and available for three forecasting horizons of 1-, 3-, and 12-month-ahead. But since our 303 predictors are quarterly, we compute the three month-average of the uncertainty indices to obtain quarterly values of the 3- and 12-month-ahead indices, with us dropping the 1-month-ahead index for obvious reasons of compatibility with quarterly data. We call the macroeconomic and financial uncertainty indices as MU1 and MU4, and FU1 and FU4 to correspond to one- and 4-quarter-ahead uncertainties respectively, i.e., short and long-run uncertainties.

Since uncertainty estimates are derived from a large data set as well, and is likely to be driven by a wide range of factors, we too rely on a high-dimensional dataset that brings together predictors from several mainstream aggregate macroeconomic and financial datasets. Our building block is the FRED-QD dataset of McCracken and Ng (2020), which we augment with stock market predictors from Welch and Goyal (2007), survey data from University of Michigan consumer surveys, commodity prices from the World Bank's Pink Sheet database, and key macroeconomic indicators from the Federal Reserve Economic Data for four economies (Canada, Germany, Japan, UK). All variables are adjusted from their respective sources for seasonality (where relevant), and removed of extreme outliers. Based on availability of data, our sample period covers 1960:Q3 to 2018:Q4.[2]

[1] The MU and FU indices are available for download from the website of Professor Sydney C. Ludvigson at: www.sydneyludvigson.com/data-and-appendixes.
[2] The data set for the predictors, and the MATLAB codes used for all the estimations, can be downloaded from the website of Professor Dimitris Korobilis at: https://sites.google.com/site/dimitriskorobilis/Research.

3.2. Empirical Results

We present the results of the point and density forecast evaluations of the four different uncertainty measures (MU1, MU4, FU1 and FU4) in Tables 1–4, respectively, for all thirteen competing autoregressive based models including the benchmark model and four out-of-sample forecast horizons [i.e. *h*=1,2,4,8]. The out-of-sample forecast horizons are so considered to examine how the models perform when forecasting both short- and long-period-ahead, and a way to ascertain the sensitivity of the results to the choice of forecast horizons. The forecasts are based on recursive estimation of 50% of the full data sample. Our interest is to ascertain how the characteristic feature of each model is likely to improve forecast of macroeconomic and financial uncertainties over the benchmark AR model. Consequently, we adjudge preference using RMSFE (Root Mean Square Forecast Error] and ALPL [Average Log-Predictive Likelihood], such that smaller values less than one and larger positive values indicate better performance of the contending model over the benchmark model, in the case of the former and latter, respectively.

Table 1: Forecast evaluation for Year-on-Year Macro Uncertainty MU1

	RMSFE				**ALPL**			
	$h = 1$	$h = 2$	$h = 4$	$h = 8$	$h = 1$	$h = 2$	$h = 4$	$h = 8$
Models with no exogenous predictors								
AR	8.57	8.85	5.59	2.50	2.54	2.62	2.80	3.11
TVPAR	1.40	3.31	3.60	2.81	-0.09	0.07	0.15	-0.27
Models with 5 factors as exogenous predictors								
FAC5	0.96	**0.87**	0.71	0.57	0.05	0.14	0.28	0.31
BAG	**0.95**	**0.87**	**0.69**	**0.52**	0.05	0.15	0.30	0.34
GPR	0.97	0.91	0.82	0.61	0.10	0.18	0.27	0.38
DMA	1.04	0.91	0.73	0.62	-0.04	-0.02	0.16	0.34
VBDVS1	1.40	1.95	1.54	2.52	0.19	0.17	0.23	**1.30**
Models with 60 factors as exogenous predictors								
SSVS	1.03	0.93	0.74	0.65	0.04	0.14	0.32	0.41
ELN1	1.15	0.97	0.75	0.68	0.04	0.21	0.42	0.50
VBDVS2	1.34	2.17	1.27	2.30	**0.21**	0.15	**0.52**	1.21
Models with all plausible macro and financial exogenous predictors								
ELN2	1.06	0.94	0.74	0.87	0.11	0.26	0.37	0.55
PLS	1.29	1.16	1.00	1.01	0.17	0.24	0.44	0.07
VBDVS3	1.18	1.57	1.60	1.90	**0.21**	**0.43**	0.07	0.81

Note: Bold entries in red show the best performing model.

Table 1 shows the RMSFE and ALPL results for the forecasts of MU1 using the competing models including the benchmark AR model. From the RMSFE result in columns 2 – 5, we find consistent outperformance of BAG over all the other models across the four specified forecast horizons, given that its ratio to the benchmark AR model is less than one and also, the smallest among the alternative forecasting models. This result may not be unconnected with the model's characteristic feature of static selection of the "best" factors (Breiman, 1996). Also, models that incorporate time-varying parameters appear to underperform compared to models that ignore the same, as can be evidently seen when TVPAR, VBDVS1, VBDVS2 and VBDVS3 are compared with the benchmark AR model across the four specified forecast horizons. Whereas, models estimated with constant parameter appear to out-perform the benchmark model. There also appears to be no strong support for incorporating a large number of exogenous predictor variables when forecasting MU1 as the first five principal component factors incorporated in the BAG model framework appear to sufficiently forecast our series of interest. Hence, the incorporation of exogenous predictors does improve forecast result but with a caveat that parsimony should be maintained or over-parameterization be avoided. The tale from the result of the forecast density differs markedly from the point forecast. The average of the logged predictive likelihood examined at $h-step$-ahead seems to suggest that the VBDVS variants proposed by Koop and Korobilis (2020) are preferred over all the alternative models, across all the out-of-sample forecast horizons. Interestingly, the second and third variants jointly out-performed the other models, and the latter doing so in shorter forecast horizons.

Table 2: Forecast evaluation for Quarter-on-Quarter Macro Uncertainty MU4

	RMSFE				**ALPL**			
	$h=1$	$h=2$	$h=4$	$h=8$	$h=1$	$h=2$	$h=4$	$h=8$
Models with no exogenous predictors								
AR	1.76	1.95	1.44	0.73	3.27	3.26	3.37	3.56
TVPAR	1.51	3.86	3.46	2.95	-0.05	0.11	0.23	0.25
Factor Models with 5 factors as exogenous predictors								
FAC5	0.90	0.79	**0.66**	0.59	0.07	0.13	0.30	0.23
BAG	**0.88**	**0.75**	0.67	**0.55**	0.08	0.15	0.27	0.25
GPR	0.91	0.83	0.75	0.72	0.12	0.22	0.35	0.21
DMA	1.00	0.84	0.71	0.63	0.00	0.04	0.25	0.36
VBDVS1	1.41	2.33	1.86	2.74	0.19	**0.23**	0.57	0.41
Factor Models with 60 factors as exogenous predictors								
SSVS	0.95	0.81	0.76	0.78	0.07	0.16	0.32	0.35
ELN1	1.06	0.87	0.73	0.73	0.06	0.21	0.34	0.41
VBDVS2	1.41	1.65	1.06	2.45	0.26	0.19	**0.60**	**1.13**
Models with all plausible macro and financial exogenous predictors								
ELN2	1.03	0.96	0.89	0.99	0.11	0.19	0.43	0.33
PLS	1.38	1.16	1.07	1.26	0.10	0.18	0.28	-0.06
VBDVS3	1.12	1.47	1.60	1.80	**0.36**	0.22	0.28	0.98

Note: See Notes to Table 1.

Turning to MU4, the RMSFE and ALPL results in Table 2 are not markedly different from those obtained for MU1. While RMSFE points to BAG as the most preferred, ALPL appears to suggest preference of the second variant of VBDVS with 60 principal component factors for longer out-of-sample forecast periods. On the other hand, taking cognizance of all the moments, ALPL results suggest that simultaneous incorporation of time-varying parameter and large number of variables could improve forecast over the benchmark and alternative models. However, ensuring parsimony may be an option that should not be overlooked.

Table 3: Forecast evaluation for Year-on-Year Financial Uncertainty [FU1]

	RMSFE				ALPL			
	h = 1	*h* = 2	*h* = 4	*h* = 8	*h* = 1	*h* = 2	*h* = 4	*h* = 8
Models with no exogenous predictors								
AR	19.18	17.30	10.64	6.31	2.08	2.14	2.39	2.67
TVPAR	1.35	1.84	2.11	2.74	-0.01	0.24	-0.04	-0.14
Factor Models with 5 factors as exogenous predictors								
FAC5	0.94	0.90	0.87	0.95	0.02	0.06	0.07	0.21
BAG	0.96	0.91	0.82	0.80	0.03	0.07	0.09	0.21
GPR	1.00	1.04	1.01	0.97	0.05	0.07	0.02	0.10
DMA	1.03	0.97	0.94	0.99	-0.07	-0.02	-0.05	0.03
VBDVS1	1.30	1.76	1.71	1.74	0.23	0.31	**0.56**	0.32
Factor Models with 60 factors as exogenous predictors								
SSVS	0.93	0.83	**0.71**	**0.85**	0.04	0.09	0.11	0.24
ELN1	**0.92**	0.88	0.75	**0.85**	0.05	0.12	0.17	0.20
VBDVS2	1.38	1.61	1.95	1.79	0.23	0.40	0.31	0.63
Models with all plausible macro and financial exogenous predictors								
ELN2	**0.92**	**0.81**	0.80	1.26	0.13	0.15	0.17	0.18
PLS	1.07	0.91	0.80	0.98	0.14	-0.01	0.33	0.17
VBDVS3	1.23	1.32	1.60	1.49	**0.40**	**0.61**	0.46	**0.81**

Note: See Notes to Table 1.

With regard to FU1 forecast, we again find models incorporating time-varying parameters to underperform the benchmark, when compared to alternative models that do not incorporate time-variation, adjudging by the RMSFE results (see Table 3). It appears that SSVS, ELN1 and ELN2 jointly out-performed the benchmark model and all other alternative models as they all were preferred in two out-of-sample forecast horizons. Generally, the ELN model framework is most precise in producing point forecast for FU1, while simultaneous incorporation of time-varying parameters and large number of exogenous predictors may produce the least precise point forecast for the series in question. Like the macroeconomic uncertainty forecasts, a consideration of the ALPL results (Table 3) however shows that VBDVS variants are preferred over the benchmark model and other alternative models, and this imperatively means that these models, especially VBDVS3, could produce better density forecast than any of the alternative models.

Table 4: Forecast evaluation for Quarter-on-Quarter Financial Uncertainty [FU4]

	RMSFE				ALPL			
	$h = 1$	$h = 2$	$h = 4$	$h = 8$	$h = 1$	$h = 2$	$h = 4$	$h = 8$
Models with no exogenous predictors								
AR	1.63	1.66	1.17	0.76	3.27	3.29	3.51	3.78
TVPAR	1.35	1.82	2.16	2.89	-0.02	0.20	-0.21	-0.06
Factor Models with 5 factors as exogenous predictors								
FAC5	0.91	0.87	0.84	0.94	0.03	0.04	0.07	-0.02
BAG	0.93	0.87	0.79	**0.78**	0.04	0.04	0.09	0.10
GPR	1.01	0.96	0.98	0.95	0.07	0.04	0.04	-0.13
DMA	1.01	0.92	0.90	0.98	-0.09	-0.06	-0.06	-0.18
VBDVS1	1.31	1.59	1.59	1.63	0.19	0.19	**0.38**	0.11
Factor Models with 60 factors as exogenous predictors								
SSVS	0.92	0.82	**0.71**	0.85	0.05	0.09	0.13	**0.14**
ELN1	0.93	0.86	0.74	0.82	0.03	0.10	0.16	0.10
VBDVS2	1.48	1.50	1.66	1.72	0.18	0.32	0.12	-0.01
Models with all plausible macro and financial exogenous predictors								
ELN2	**0.89**	**0.81**	0.82	1.29	0.12	0.15	0.15	-0.24
PLS	1.08	0.91	0.82	1.01	0.03	-0.04	0.13	-0.55
VBDVS3	1.20	1.30	1.59	1.50	**0.22**	**0.41**	0.21	0.07

Note: See Notes to Table 1.

On the FU4 forecasts, ELN2 appears to be the preferred model, producing the most precise point forecast at short-run horizons, than the benchmark model or any other alternatives (see Table 4). This stance supports the incorporation of a large number of exogenous predictors as they tend to provide some information that could be useful for point forecast of financial uncertainty. On the density forecast alternative, VBDVS3 is mostly preferred, as has been consistently the case across uncertainty measures. It appears that there are contradicting stances between the point and density forecast precision measures, however, the VBDVS performs better consistently across uncertainty measures when the density forecast is considered, while for the point forecast models incorporating time-varying parameters are not supported by the data. Put differently, for point forecast of macroeconomic and financial uncertainties, BAG and ELN are the models that seem to be preferred by the data, respectively.

One clear conclusion from the various findings is that allowing for additional predictors in the benchmark model [AR(4)] when forecasting MU and FU (albeit with varying numbers for the series in question) tends to offer better forecast outcomes regardless of the choice of proxy for uncertainty and the forecast metric.

4. Conclusion

Uncertainty is known to impact the economic variables and financial markets, hence timely and accurate forecasting of uncertainty is invaluable to policymakers and investors as well in gauging the future path of the overall economy. Given this, we forecast macroeconomic and financial uncertainties of the US over the period of 1960:Q3 to 2018:Q4, based on a large data set of 303 predictors using a wide array of constant parameter and time varying models. We find that uncertainty is indeed forecastable based on a wide set of variables encompassing various sectors of the US economy, commodity and international markets. Interestingly, accurate point forecasts can be achieved without incorporating time-variation in the parameters of the relatively small- and large-scale models for macroeconomic and financial uncertainties respectively. However, time-variation and large number of predictors are indeed important requirements when producing precise density forecasts. With density forecasts now considered more important by policymakers than point forecasts, we find that the recently proposed variational Bayes algorithm designed for computationally efficient posterior and predictive inference in time-varying parameter models is the standout performer. Since uncertainties are forecastable, it also implies that when identifying an uncertainty shock in structural macroeconometric model to analyse its impact on other economic variables via impulse response functions, econometricians must be cognizant of the fact that, uncertainties cannot be treated as an exogenous variable, especially financial uncertainty, as it is generally affected by large number of predictors – a result in line with Carriero et al., (2018).

As part of future research, it would be interesting to extend our forecasting exercise to similar broad measures of uncertainty indicators available for other advanced and emerging market economies (see for example, Miescu (2019)).

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