SHORT-TERM MACROECONOMIC FORECASTS FOR THE U.S. ECONOMY USING NOWCASTS OF THE SURVEY OF PROFESSIONAL FORECASTERS*

*Inês Maria Gonçalves***

ABSTRACT

This paper proposes a forecasting strategy for a set of macroeconomic variables using information from surveys to professional analysts. Specifically, it is assumed that certain forecasts for the current state of the economy (nowcasts) are very difficult to beat in the short-term, so that there are benefits in including them in the time series of the variables to predict. For the U.S. economy, the Survey of Professional Forecasters (SPF) of the Federal Reserve Bank of Philadelphia is a renowned source of nowcasts and is therefore the starting point chosen to predict seven macroeconomic variables of interest. Using several models, both univariate and multivariate, it is possible to compare the forecasts that result from the use of this strategy with the predictions that would be obtained if the series did not include the additional information. Moreover, the performance of the models with nowcasts is compared with the predictions of the survey professional themselves. While the SPF asserts itself as highly reliable, the nowcasts appear to contribute for increasing the accuracy of the models used. Although sensitive to the choice of variables, the approach proposed in this paper proves to be quite promising and paves the way for further research, namely the application to other variables and/or economies.

1. Introduction

The development of sharper forecasting methods plays a key role in supporting the formulation of economic policy. Given the lag with which policies impact on the economy, the decision-making process involves evaluating the expected, rather than the present behaviour of the variables of interest. Central banks assume a major responsibility in the continuous improvement of these methods, as their forecasts provide analysts and policy makers with informed visions on the future evolution of the economy.

This paper describes a strategy for enhancing some standard forecasting models through the use of timely information about the variables to predict, in line with Faust and Wright (2007). Explicitly, the available time series are extended with forecasts for the current period, conferring to the models a non-negligible informational advantage. These forecasts are the so-called nowcasts, defined as forecasts produced in t for any given macroeconomic variable in t.[1]

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** Banco de Portugal, Economics and Research Department.

1 The production of nowcasts, commonly referred to as nowcasting, falls outside the scope of this paper. For more information on the topic, see for instance Giannone *et al*. (2008) and Banbura *et al*. (2010).

The contribution of this paper is primarily to complement the research presented in Valle e Azevedo and Pereira (2013). That is to say, using the same models used in the foregoing, it is shown that the Low Pass Filter used by the authors has a generally superior performance compared with the other methods considered. A distinctive aspect of this paper is that it assesses the behaviour of the models in a context where the time series include additional observations, the nowcasts, comparing the results with those using only the observed data.

Beyond the Low Pass Filter, other univariate and multivariable models are used, as well as forecast combination methods, seeing that one should take advantage from forecasts containing different information. In this field, refer to the works of Chong and Hendry (1986), Diebold and Mariano (1995) and Harvey *et al*. (1998). Finally, based on the idea that there is a relatively limited set of factors that determine the behaviour of many macroeconomic variables, factor models are also used (see Stock and Watson (2002), for example).

The models are (re)estimated in each period t, in order to reproduce the data release calendar in real time. Thus, the paper simulates an out-of-sample forecasting context, wherein the models are estimated with the observed data up to t. This is common practice in the literature (see Angelini *et al*. (2011) or Valle e Azevedo and Pereira (2013), among others). More precisely, the approach of the paper may be characterised as pseudo out-of-sample, since it considers only final data vintages, therefore ignoring potential data revisions.

The article focuses on the U.S. because this is an extensively studied economy, to which the models used here have already been applied, thus ensuring their suitability. Additionally, the ease of access and availability of data favour the option for analysing this economy.

As regards the source of nowcasts, the paper chooses the Survey of Professional Forecasters (SPF) of the Federal Reserve Bank of Philadelphia, because it allows for making use of a publicly accessible and readily available set of predictions, which are considered reliable for the U.S. economy. This is a quarterly survey that includes a panel of financial analysts, whose anonymity is preserved thus ensuring their independence. According to Croushore (1993), these characteristics make the SPF very hard to beat when compared with other surveys. In fact, similar surveys have some disadvantages, such as disclosure only twice a year (Livingston Survey), forecasts in annual average terms (National Association of Business Economists Outlook), or the use of a panel of known analysts (Blue Chip Forecast). In addition, as shown by Stark (2010), the SPF tends to behave well at short horizons. Since the article focuses on forecasts up to four quarters, this survey was considered the most appropriate for the study.

In terms of variables, the article presents forecasts for real Gross Domestic Product (GDP), Consumer Price Index (CPI), GDP deflator, civilian unemployment rate, 3-month T-bill rate, residential investment and housing starts. The forecasts are evaluated based on the root mean square prediction error (RMSE), with the forecast error defined as the difference between the predicted value and the observed value of the variable. Additionally, the paper provides a qualitative description of the relative performance of the models over time.

The paper is organised as follows. The next section presents briefly the different types of models and methods used to produce forecasts. Then, section 3 describes the data, characterising the variables and the sample. Section 4 discusses the results. Finally, section 5 summarises the conclusions and points out ways for future research. In complement to section 2, the paper includes an appendix where the forecasting techniques are developed a little further, in particular with respect to the mathematical formalisation.

2. Forecasting Models and Methods

The forecasts are built based on standard models in the literature. In particular, the article follows the approach of Faust and Wright (2007) and Valle e Azevedo and Pereira (2013). In this section, the various types of models used in the production of forecasts are introduced, giving primacy to the intuitive explanation behind their use and referring the reader to the appendix for more details concerning the mathematical formalisation.

Firstly, the article considers models that produce forecasts based on the observed data, by means of a relationship between the past and future values of the variables to predict. These are called **Autoregressive Models** (or univariate models), since the future behaviour of the variables is explained by their behaviour in the past. The approach is therefore quite simple, as the variables depend only on themselves. Three alternative models are used: **Iterated Autoregression (IAR)**, **Direct Autoregression (DAR)** and **Random Walk (RW)**.

Secondly, some complexity is introduced, as the models are augmented with additional variables (indicators). It is therefore recognised that there are other elements likely to influence the behaviour of a given economic variable beyond itself. A mathematical model that establishes a relationship between the variables to predict, the same variables in previous periods (like in Autoregressive Models) and one of the indicators (for the current period) included a panel that is presented in the next section is then built. The approach taken in the article is to combine the forecasts obtained with each of the indicators, since it is believed that it is possible to obtain benefits from incorporating distinct information. These are therefore the **Forecast Combination Methods**, among which two specifications are considered: **Equal Weighted Averaging (EWA)**, which calculates a simple average of the forecasts, and **Bayesian Model Averaging (BMA)**, where the weights assigned to each prediction in the average are chosen according to Bayesian statistics.

A third type of models fine-tunes the technique described in the above paragraph, by summarising the effect of the indicators through their principal components. Explicitly, the information contained in the panel of indicators is synthesised based on the idea that the behaviour of those additional variables is largely determined by a more restricted set of common factors. These models are then called Factor Models and the paper also considers two specifications: **Factor Augmented Vector Autoregression (FAVAR)** and **Direct Factor Augmented Autoregression (DFAAR)**.

Finally, forecasts are computed using the **Low Pass Filter**. This method, used in Valle e Azevedo and Pereira (2013) seeks to capture the lowest frequencies of the time series of interest, since the high frequencies tend to contain a high level of noise, which makes them difficult to predict. Thus, the variables are estimated by means of a smoothed version of themselves obtained after the application of a filter that eliminates fluctuations over an optimal frequency. The specifications used can be classified within each of the classes of models previously described: **Univariate Specification (Filter)**, **Forecast Combination (Combination)** and **Specification with Factors (Filter with Factors)**.

3. Data

The forecasts cover seven U.S. macroeconomic variables, namely real GDP, CPI, GDP deflator, civilian unemployment rate, 3-month T-bill rate, residential investment and housing starts. Forecasts are computed quarterly for horizons from one up to four quarters, *i.e.*, up to one year after the initial forecasting period. The predictions are then compared with the median of the quarterly SPF forecasts. The sample ranges from the fourth quarter of 1968, corresponding to the first release date of the SPF, to the third quarter of 2012. In each quarter t, the models are estimated with the available data up to t, with the initial forecasting period set to the first quarter of 1984, the beginning of the "Great Moderation". Thus, the paper simulates a real time forecasting context (out-of-sample). However, the exercise is simplified by using the existing vintages in the third quarter of 2012 (not annualised) extracted from the Federal Reserve Bank of Philadelphia database, regardless of later revisions.[2] With the exception of the civilian unemployment rate and the 3-month T-bill rate, to which level differences are applied, variables are transformed through the application of logarithm differences to ensure their stationarity.

The panel of indicators is essentially the same as in Valle e Azevedo and Pereira (2013), incorporating various activity indicators and monetary and financial variables.[3] However, it is worth noticing an important difference. The three-month averages that transform monthly variables into quarterly variables are calculated here from the last to the first available observation. This is done to align the information so that the data release calendar coincides with its availability to SPF analysts, allowing for recursive forecasts.

4. Results

This section discusses the results, granting particular attention to two key macroeconomic variables: real GDP, as a measure of economic activity, and the CPI, as a measure of price developments. For the sake of brevity, the results for the other variables are more concise.

The relative accuracy of the models is assessed based on the root mean square prediction error (RMSE), both in the case where the models use nowcasts as jump-offs and in the opposite.[4] To compare the forecasts, it then becomes necessary to ensure that the predictions refer to the same quarter. This implies that, at time t , the forecast for $t+1$ without nowcast is two quarters ahead, since the last available value of the time series usually refers to $t-1$. On the other hand, with the nowcast, the prediction for $t+1$ is only one quarter ahead, because in this case the forecast is computed with data up to t . This reasoning applies to forecasts for $t+h$, with $h \in \left\{1, 2, 4\right\}$ within the scope of this study.

To improve readability, the RMSE is presented as a ratio, calculated *vis-à-vis* the IAR model without nowcast, as this was considered both a simple and robust performance benchmark.[5]

The analysis is supplemented with a qualitative description of the behaviour of the models over time.

2 Data are available online at http://www.phil.frb.org/research-and-data/real-time-center/survey-of-professional-forecasters/data-files/.

3 The panel is built with data from the Federal Reserve Bank of St. Louis, available at http://research.stlouisfed.org/. For a detailed account of the indicators included in the panel as well as the transformations applied, see Valle e Azevedo and Pereira (2013). The panel in the abovementioned paper contains 83 series, whereas in this article 78 series are used. The series "Non-Borrowed Reserves of Depository Institutions" and "Real Change in Private Inventories" were eliminated due to missing observations. The series "Real Personal Consumption Expenditures: Durable Goods","Real Personal Consumption Expenditures: Services" and "Real Personal Consumption Expenditures: Nondurable Goods" were also discarded, because of mismatches in the size of the series and their decomposition. Finally, the series "Real Federal Consumption Expenditures and Gross Investment", "Real State and Local Consumption Expenditures and Gross Investment", "Real Private Nonresidential Fixed Investment" and "Real Private Residential Fixed Investment" were replaced by equivalent series available through the Federal Reserve Bank of Philadelphia at http://www.phil.frb.org/research-and-data/real-time-center/survey-of-professional-forecasters/data-files/.

4 The RMSE is calculated as $\sqrt{\frac{\sum_{t=1}^{n}\left(\hat{y}_t - y_t\right)^2}{n}}$, where n stands for the number of forecasts and $\hat{y}_t - y_t$ represents the forecast error. The lower the RMSE, the greater the accuracy of the models.

5 For each model k , the relative RMSE is computed as $\frac{RMSE_k}{RMSE_{IAR\ without\ nowcast}}$. Whenever the relative RMSE is smaller than 1, model k generates more accurate predictions than the IAR model without nowcast. The smaller the ratio, the better the performance of model k .

4.1. Root mean square prediction error

The evaluation suggests that the proposed strategy translates into generally superior forecasts. This should not come as a surprise, as using the nowcasts confers an important informational advantage to the models compared with the predictions produced without nowcasts. Nevertheless, there is some sensitivity to the choice of variables. Another result is that the jump-offs appear to have an uneven effect, in the sense that the performance of the weakest models improves relatively more compared to the SPF.

Table 1 presents the results for real GDP. For $t+1$ and $t+2$, SPF forecasts outperform those of the models, even after the addition of nowcasts. However, for $t+4$, the IAR and DAR models with nowcasts generate more precise predictions, suggesting some dilution of SPF's advantage for longer horizons. Furthermore, excepting the DAR model (for $t+1$) and the Factor Models (for $t+2$ and $t+4$), the lengthening of the available time series results in smaller forecast errors. Thus, there are *de facto* gains from using this strategy, especially for models with poorer performances.

Table 1

RELATIVE ROOT MEAN SQUARE ERROR: REAL GDP

	t+1		t+2		t+4	
	Without nowcast	With nowcast	Without nowcast	With nowcast	Without nowcast	With nowcast
Autoregressive Models						
IAR	1.000	0.985	1.000	0.976	1.000	**0.994**
DAR	0.998	1.003	1.003	0.975	1.037	0.995
RW	1.138	1.037	1.282	0.997	1.369	1.084
Forecast Combination Methods						
EWA	0.996	0.978	1.005	0.980	1.055	1.024
BMA	1.028	0.983	1.059	1.005	1.074	1.045
Factor Models						
FAVAR	1.100	1.096	1.074	1.096	1.082	1.095
DFAAR	1.056	1.035	1.059	1.076	1.059	1.061
Low Pass Filter						
Filter	1.030	0.998	1.061	1.021	1.059	1.042
Combination	1.012	0.990	1.043	1.011	1.059	1.042
Filter with Factors	1.019	1.006	1.044	1.030	1.053	1.040
SPF	**0.949**	-	**0.970**	-	1.006	-

Source: Author's calculations.
Notes: For each horizon, the top three models are shaded and the best model is marked bold.

Turning to the CPI (Table 2), the relative RMSE is always lower for the models with nowcasts, indicating that the benefits from using the jump-offs are higher than those for real GDP. Still, the reduction in RMSE continues to be more pronounced in the models with poorer performance *a priori*. Despite the improvement, the forecasts produced by the models fail to overcome the SPF in any of the horizons studied. Nevertheless, it should be noted that the relative advantage of SPF decreases once again with the forecast horizon. In contrast to the experience for real GDP, the Low Pass Filter has a superior performance compared with the other models considered, positioning itself as the most serious challenger to the SPF.

Even if these results do not point to clear benefits in using the nowcasts, there were more visible gains for the other variables. Though not as fundamental, those variables are also very important for the analysis of the economy. Their results are now presented.

Table 2

RELATIVE ROOT MEAN SQUARE ERROR: CPI

	$t+1$		$t+2$		$t+4$	
	Without nowcast	With nowcast	Without nowcast	With nowcast	Without nowcast	With nowcast
Autoregressive Models						
IAR	1.000	0.878	1.000	0.953	1.000	0.953
DAR	0.981	0.878	0.999	0.954	1.142	1.022
RW	1.109	0.853	1.059	0.894	1.072	0.909
Forecast Combination Methods						
EWA	0.980	0.881	1.000	0.950	1.090	0.985
BMA	1.081	0.905	1.088	1.038	1.311	1.149
Factor Models						
FAVAR	1.049	0.932	1.067	0.970	1.045	1.002
DFAAR	1.043	0.898	1.034	1.017	1.057	1.031
Low Pass Filter						
Filter	0.834	0.799	0.798	0.798	0.801	0.794
Combination	0.830	0.800	0.811	0.803	0.832	0.815
Filter with Factors	0.828	0.797	0.827	0.808	0.862	0.834
SPF	**0.754**	-	**0.761**	-	**0.785**	-

Source: Author's calculations.

Notes: For each horizon, the top three models are shaded and the best model is marked bold.

Since the use of nowcasts in models for real GDP and CPI tends to increase forecast accuracy, the results for the other variables focus on these versions alone. At the same time, the group of models considered is also limited, maintaining the IAR model, as the benchmark, the EWA model, for the consistency in performance, and all versions of the Low Pass Filter, due to the superior behaviour in forecasts for the CPI. On the other hand, Factor Models are eliminated from the analysis as the results were somewhat disappointing for the variables already characterised.

Table 3 details the relative RMSE. As a rule, the Low Pass Filter now surpasses the SPF, whose primacy is not apparent anymore. In fact, although the specifications may vary, the Low Pass Filter becomes the preferred forecasting method, regardless of the variable or horizon. This result further strengthens the conclusions of Valle e Azevedo and Pereira (2013), where the use of this method, even without nowcasts, resulted already in very competitive predictions compared to the SPF.

As such, the experience of the whole set of variables studied leaves evidence that the quality of the predictions obtained when the models use the SPF nowcasts as a starting point, or jump-off, is higher than otherwise.

4.2. Behaviour over time

The analysis of the previous subsection, focused on the relative RMSE, was of a static nature, justifying the inclusion of a qualitative description of the overall performance of the models over time. Indeed, one needs to take into account the possibility that the preceding results may depend on the sample, meaning that there may be variations in the behaviour of different forecasts. This subsection tackles this issue, emphasising stability aspects throughout the sample.

A general result is the persistence of significant differences between variables. Another observation relates to the performance of the models during the financial crisis, particularly in the fourth quarter of 2008 and the first quarter of 2009, when the biggest differences relative to the SPF are recorded. In the case of real GDP, there is a high degree of instability over time and the relative performance deteriorates substantially with the crisis. As for CPI models, the profile is of great stability throughout the sample, but the crisis period also determines a degradation in the quality of the predictions against the SPF, particularly marked at shorter horizons. However, for the remaining variables the results are once again more

Table 3

RELATIVE ROOT MEAN SQUARE ERROR: OTHER VARIABLES (WITH NOWCASTS)

	t+1	t+2	t+4
GDP Deflator			
IAR	0.994	1.009	0.990
EWA	0.964	0.981	1.133
Low Pass Filter			
Filter	**0.871**	**0.846**	**0.725**
Combination	0.872	0.875	0.799
Filter with Factors	0.904	0.901	0.863
SPF	1.002	0.986	0.896
Unemployment Rate			
IAR	0.929	0.924	0.989
EWA	0.929	0.911	0.972
Low Pass Filter			
Filter	0.927	0.885	0.917
Combination	**0.909**	**0.860**	**0.886**
Filter with Factors	0.931	0.879	0.908
SPF	1.052	1.077	1.254
3-Month T-Bill Rate			
IAR	0.881	1.092	0.979
EWA	0.875	1.131	1.008
Low Pass Filter			
Filter	0.812	0.965	0.979
Combination	**0.809**	**0.964**	**0.978**
Filter with Factors	0.824	0.985	0.990
SPF	0.953	1.308	1.431
Residential Investment			
IAR	0.964	0.980	0.997
EWA	0.940	0.936	0.992
Low Pass Filter			
Filter	0.948	0.921	0.897
Combination	0.920	0.911	0.892
Filter with Factors	0.928	**0.897**	**0.884**
SPF	**0.913**	0.953	0.973
Housing Starts			
IAR	0.980	0.981	1.002
EWA	0.971	0.971	1.002
Low Pass Filter			
Filter	0.943	0.941	0.959
Combination	**0.941**	0.938	0.959
Filter with Factors	0.943	**0.934**	**0.955**
SPF	0.949	1.047	1.063

Source: Author's calculations.

Notes: For each horizon, the top three models are shaded and the best model is marked bold.

encouraging, with performances equivalent or superior to the SPF and even improved accuracy during the quarters of the crisis. In fact, except for the GDP deflator (whose models consistently outperform the SPF and do not register significant breaks along the sample) and the unemployment rate (for which there is a deterioration only in the quarters of the crisis), the variables tend to improve over the SPF, a trend that is especially evident at longer horizons.

This analysis thereby confirms the results obtained with the relative RMSE in the considered sample.

5. Conclusions

This paper proposes a strategy that seeks to incorporate SPF nowcasts in short-term forecasting models for the U.S. economy. Generally, this approach proves to be quite promising, since there is a reduction of forecast errors in models that make use of this additional information. Furthermore, the paper shows that, by lengthening the available time series, it is possible to compute more accurate forecasts than those of the SPF for the majority of variables, especially in longer horizons. The analysis of the stability of the results over the sample complements and confirms that of the RMSE, suggesting indeed a tendency of improvement against the SPF for most variables, yet not immune to shocks such as the episode of the financial crisis beginning in 2008.

With this paper, the findings of Valle e Azevedo and Pereira (2013) are reinforced, since the Low Pass Filter used by those authors proves to be a capable and consistent forecast method. Actually, except for GDP forecasts, the Low Pass Filter is the strongest candidate to beat the SPF, although the results do not allow for identifying a single specification for all variables. Among the other models studied, it is worth emphasising the good performance of the simplest models, particularly the IAR, and the EWA forecast combination method.

Two aspects, though, make the experience of the paper somewhat inconclusive. In fact, not only the results depend on the variable to forecast, but it seems that the nowcasts have an uneven effect on the models. Moreover, the asymmetry is contrary to what would be desirable, in the sense that the worst models take the greatest advantage, implying that the improvement of the best models, which would be the primary objective of the study, is comparatively smaller.

In any case, the paper justifies the extension of the analysis in order to fine-tune the results achieved, paving the way for further research, namely through the application to a larger set of variables and to other economies, such as the euro area, and also by using forecasts from other sources besides the SPF.

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Appendix: Forecasting Models and Methods (Mathematical Formalisation)

This appendix develops and complements section 2, by formalising the models and methods used to produce forecasts. The chosen specifications, in particular regarding the lag order criteria, are those that result in the best performance of the different models, and alternative specifications do not significantly alter the results.

AUTOREGRESSIVE MODELS

- **Iterated Autoregression Model (IAR)**: The equation $y_t = \rho_0 + \sum_{j=1}^{p} \rho_j \, y_{t-j} + \varepsilon_t$ is estimated by Ordinary Least Squares (OLS), with the lag order given by $p = 4$.

- **Direct Autoregression Model (DAR)**: For each horizon, h, $y_{t+h} = \rho_{0,h} + \sum_{j=1}^{p} \rho_{j,h} \, y_{t+1-j} + \varepsilon_{t+h}$ is estimated by OLS, with the lag order chosen according to the Akaike information criterion.

- **Random Walk Model (RW)**: The random walk model simply forecasts y_{t+h} as y_t.

FORECAST COMBINATION METHODS

- The forecast combination methods start by estimating the same model, given by the equation $y_{t+h}^{i} = \rho_{0,h}^{i} + \sum_{j=1}^{p} \rho_{j,h}^{i} \, y_{t+1-j} + \beta_{i,h} \, x_{it} + \varepsilon_{t+h}^{i}$, where $i = 1, \dots, n$ and $\left\{x_{it}\right\}_{i=1}^{n}$ represents the panel of indicators described in the main text. The specifications used were the following.

- **Equal Weighted Averaging (EWA)**: This method calculates a simple average of the forecasts obtained with the estimation of the model just described, in which the lag order is fixed with $p = 4$.

- **Bayesian Model Averaging (BMA)**: In this method, the weights attributed to each of the predictions when calculating the average are chosen according to Bayesian statistics. As an assumption, each model M_i is assigned a constant probability, given by $P\left(M_i\right) = n^{-1}$. According to Fernandez *et al.* (2001), it is further assumed that $\varepsilon_{t+h}^{i} \sim N\left(0, \sigma^2\right)$ and that the prior distribution of $\lambda_{i,h} = \left[\rho_{0,h}^{i} \; \rho_{1,h}^{i} \cdots \rho_{p,h}^{i} \; \beta_{i,h}\right]$, conditional on σ, is given by $N\left(\bar{\lambda}_h, \phi\left(\sigma^2 \sum_{t=1}^{T}\left(w_{it} \, w_{it}^{'}\right)^{-1}\right)\right)$, where $w_{it} = \left[1 \; y_t \; y_{t-1} \cdots y_{t+1-p} \; x_{it}\right]$ and the marginal prior distribution of σ is proportional to $1/\sigma$. ϕ is a hyperparameter that determines the level of information given by the prior. For each horizon, the value of ϕ is the same as in Valle e

Azevedo and Pereira (2013).[6] $\bar{\lambda}_h$ follows from the estimation of the parameters in a subsample ranging from the fourth quarter 1968 to first quarter of 1984.[7] After estimating each model, the mean of the posterior distribution of $\lambda_{i,h}$, given by $\tilde{\lambda}_{i,h} = \frac{\hat{\lambda}_{i,h\phi}}{1+\phi} + \frac{\bar{\lambda}_{i,h\phi}}{1-\phi}$ (where $\hat{\lambda}_{i,h}$ is the OLS estimate of $\lambda_{i,h}$ for each M_i), is used to compute forecasts for y_{t+h}, as $\hat{y}^i_{t+h|t} = \tilde{\lambda}'_{i,h}\, w_{it}$. The BMA forecast is finally given by $\hat{y}_{t+h|t} = \sum_{i=1}^{n} P\left(M_i \big/ D\right) \hat{y}^i_{t+h|t}$, with $P\left(M_i \big/ D\right)$ representing the probability, given the sample D, that model i is the true model.

FACTOR MODELS

- **Factor Augmented Vector Autoregression (FAVAR)**: This method estimates the FAVAR model presented in Bernanke *et al.* (2005), given by $\zeta_t = \phi_0 + \sum_{j=1}^{s} \phi_j\, \zeta_{t-j} + \varepsilon_t$, where $\zeta_t = \left(y_t, z_{1t}, z_{2t}, \ldots, z_{mt}\right)'$ and y_{t+h} is estimated by iterating the model. $\left\{z_{it}\right\}_{i=1}^{m}$ are the first m principal components of the set of indicators $\left\{x_{it}\right\}_{i=1}^{n}$. The lag order, s, is of one quarter and the first three principal components are used ($m = 3$).

- **Direct Factor Augmented Autoregression (DFAAR)**: This model corresponds to the DAR model presented previously, but augmented with factors. It should be noted that the factors used, $\left\{z_{it}\right\}_{i=1}^{m}$, are exactly the same entering the FAVAR model. For each horizon, $y_{t+h} = \rho_{0,h} + \sum_{j=1}^{p} \rho_{j,h}\, y_{t+1-j} + \sum_{j=0}^{p} \sum_{i=1}^{m} \gamma_i\, z_{it-j} + \varepsilon_{t+h}$ is estimated by setting the parameter m to 3. The lag order, p, is determined by the Akaike information criterion for both the dependent variable and the factors.

LOW PASS FILTER

This method proposes the estimation of y_{t+h} through a smoothed version, $y^{Low\ Frequency}_{t+h} = B(L)\, y_{t+h}$, where $B(L) = \sum_{j=-\infty}^{\infty} B_j\, L^j$ is the filter that eliminates fluctuations above an optimal frequency determined in Valle e Azevedo and Pereira (2013).[8] The specifications considered follow.

- **Univariate Specification (Filter)**: The forecasts are produced by solving the optimisation problem: $\min_{\alpha_0, \left\{\overline{B}^p_j\right\}_{j=0,\ldots,p}} E\left[\left(y^{Low\ Frequency}_{T+h} - \hat{y}^{Low\ Frequency}_{T+h}\right)^2\right]$, using the appropriate $\left\{\widehat{B}^p_j\right\}_{j=0,\ldots,p}$ in $\hat{y}^{Low\ Frequency}_{t+h|t} = \alpha_0 + \sum_{j=0}^{p} \widehat{B}^p_j\, y_{t-j}$ and adjusting p so that $p = 50 - h$.

6 See Valle e Azevedo and Pereira (2013).

7 See section 3 of the main text for more details about the sample.

8 See Valle e Azevedo and Pereira (2013).

- **Forecast Combination (Combination):** Taking each of the $\left\{x_{it}\right\}_{i=1}^{n}$ indicators considered, n forecasts for y_{t+h} are calculated with the Low Pass Filter, and then combined using a simple average.
- **Specification with Factors (Filter with Factors):** Augments the model with the same $\left\{z_{it}\right\}_{i=1}^{m}$ factors used in the models outlined above.