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The analyses, opinions and findings of these papers represent the views of the authors, they are not necessarily those of the Banco de Portugal or the Eurosystem

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Macroeconomic Forecasting Starting from Survey Nowcasts[*]

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Abstract

We explore the use of nowcasts from the Philadelphia Survey of Professional Forecasters as a starting point for macroeconomic forecasting. Specifically, survey nowcasts are treated as an additional observation of the time series of interest. This simple approach delivers enhanced model performance through the straightforward use of timely information. Important gains in forecast accuracy are observed for multiple methods/models, especially at shorter horizons. Still, given that survey nowcasts are very hard to beat, this approach proves most useful as a means of developing a sharper forecasting routine for longer-term predictions.

JEL Classification: C14, C32, C51, C53

Keywords: Macroeconomic Forecasting, Professional Forecasters, Low-frequency Filtering

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1 Introduction

This paper considers survey nowcasts as a starting point for macroeconomic forecasting methods not suited to nowcasting or very short-term forecasting. Instead of attempting to summarize numerous indicators into an up-to-date prediction, the strategy is to outsource a reliable nowcast and take it as an additional observation in the dataset. By incorporating timely information on the current state of the economy, this grants traditional methods an informational bonus effortlessly, contrasting with the work of, among others, Angelini et al. (2011), Clements and Galvão (2008, 2009), Andreou et al. (2011), Giannone et al. (2008) or Liebermann (2013), whose focus lies in the definition of an appropriate nowcasting framework.

Surprisingly, as far as we are aware, only Faust and Wright (2009) and Wolters (2013) perform an analysis similar to ours but using the US Federal Reserve Greenbook forecasts, which are released to the public with a lag of around five years. The former authors focus on statistical models and forecasts for real GDP, GDP and CPI inflation while the latter focuses on DSGE models and forecasts for real GDP, the Fed funds rate and GDP inflation. By contrast, we use nowcasts from the Philadelphia Survey of Professional Forecasters (SPF, henceforth), which are readily and publicly available around the middle of each quarter and fare very well compared with competing statistical methods as well as with structural models and alternative surveys, see e.g., Croushore (1993, 2008), Ang et al. (2007), Faust and Wright (2012), Stark (2010), Baghestani (2009, 2012), Rubaszek and Skrzypczynski (2008) or Kolasa et al. (2012). Further, we cover seven US macroeconomic time series which are widely used to monitor the business cycle: real GDP and the unemployment rate (real activity), residential investment and housing starts (housing market), CPI and GDP inflation (inflation) as well as the 3-month treasury bill rate. Like Faust and Wright (2009) we focus on statistical methods, several of them analyzed by those authors. Additionally, we assess thoroughly the behavior of a univariate low-frequency filter (low-pass filter, henceforth), which complements the results in Valle e Azevedo and Pereira (2013). As in Altissimo et al. (2010), the idea behind the filter is to forecast a time series by targeting only its lowest frequencies, as aiming to fit high frequencies often carries losses in terms of efficiency, especially at long horizons. Since this approach is arguably not suited for short-term forecasting, coupling it with an efficient nowcast is warranted.

In a nutshell, the paper shows that simply incorporating current quarter SPF nowcasts enhances forecast accuracy and that the low-pass filter behaves well in this context, being overall the most competitive alternative to the SPF.

The outline of the paper is as follows: Section 2 discusses the forecasting models and methods used. Section 3 presents the main results of our pseudo out-of-sample forecasting exercise, along with several robustness checks. Section 4 concludes.

2 Forecasting models and methods

Take a time series y_t and suppose one wishes to forecast y_{t+h} using information until time t. At time t, y_t is generally not available. Our approach amounts simply to appending to the available series, say $(y_1, y_2, ..., y_{t-k})$, with $k > 0$, the survey based forecasts of $y_{t-k+1}, ..., y_t$. In this paper we focus on extending the series with the nowcasts of y (i.e., $k = 1$) from the oldest survey of professional forecasters, the Philadelphia SPF.

Given these appended nowcasts, we are left with an extended time series to which we fit a forecasting model. We will compare the forecasts obtained in this fashion with forecasts that use only the available data, $(y_1, y_2, ..., y_{t-k})$, with $k > 0$.

We now describe the forecasting models and methods used:

- *Random walk (RW)*

  RW forecasts consist of taking $\hat{y}_{t+h|t} = y_{t-k}$ (where k can be greater than 0 if there are release delays) as the forecast of y_{t+h} for all h. Obviously, the forecast obtained with the series extended with survey nowcasts is just the nowcast itself for the various horizons.

- *Iterated autoregression (IAR)*

  We estimate $y_t = \rho_0 + \sum_{j=1}^{p} \rho_j y_{t-j} + \varepsilon_t$ by OLS. The h-quarters ahead forecast at time t is given by:

$$\hat{y}_{t+h|t} = \hat{\rho}_0 + \sum_{j=1}^{p} \hat{\rho}_j \hat{y}_{t+h-j|t}$$

  where $\hat{y}_{i|t} = y_i$ for $i \leq t$. We set p to 4 in all cases, as suggested by results in Marcellino et al. (2006) for quarterly data.[1]

[1] In any case, we have verified that using the AIC or BIC criteria to choose the lag order does not change significantly the results.

- *Direct autoregression (DAR)*

We estimate the parameters of the equation $y_{t+h} = \rho_{0,h} + \sum_{j=1}^{p} \rho_{j,h} y_{t+1-j} + \varepsilon_{t+h}$ by OLS with lag order chosen by the AIC criterion (maximum lag order set equal to 6). The forecast of y_{t+h} is then constructed as:

$$\hat{y}_{t+h|t} = \hat{\rho}_{0,h} + \sum_{j=1}^{p} \hat{\rho}_{j,h} y_{t+1-j}$$

Methods that incorporate other series are the following:

- *Direct factor augmented autoregression (DFAAR)*

We augment an autoregression with the first m principal components, $\{z_{it}\}_{i=1}^{m}$, of a set of n predictors, $\{x_{it}\}_{i=1}^{n}$, see Stock and Watson (2002a and 2002b). More specifically, we use the following regression to construct the h-quarters ahead forecasts:

$$y_{t+h} = \rho_{0,h} + \sum_{j=1}^{p} \rho_{j,h} y_{t+1-j} + \sum_{i=1}^{m} \sum_{j=1}^{p_i} \gamma_i z_{it-j} + \varepsilon_{t+h}$$

We set the lag orders p and p_i, $i = 1, ..., m$ using the AIC criterion (maximum lag order set equal to 6) and the number of factors m to 3. Parameters are estimated by OLS and the first m principal components are the first m eigenvectors of the variance-covariance matrix of the set of predictors. A complete description of the predictors used in the forecasting exercise is provided in the data appendix.

- *Factor augmented vector autoregression (FAVAR)*

Following Bernanke et al. (2005), we estimate $\zeta_t = \phi_0 + \sum_{j=1}^{s} \phi_j \zeta_{t-j} + \varepsilon_t$, where $\zeta_t = (y_t, z_{1t}, z_{2t}, \ldots, z_{mt})'$, and compute the forecasts of y_{t+h} by iterating the model forward. We set s and m equal to 1 and 3, respectively, as in Faust and Wright (2009). We highlight that the $\{z_{it}\}_{i=1}^{m}$ are the ones used in DFAAR method.

- *Equal-weighted averaging (EWA)*

This is a pooling forecast resulting from an average of n forecasts of y_{t+h}. Each forecast is computed from an estimated (by OLS) direct augmented autoregression $y_{t+h} = \rho_{0,h}^{i} + \sum_{j=1}^{p} \rho_{j,h}^{i} y_{t+1-j} + \beta_{i,h} x_{it} + \varepsilon_{t+h}^{i}$ for $i = 1, \ldots, n$ where p equals 4 and x_{it} is a predictor included in the panel used to extract principal components. Finally, the *EWA* forecast of y_{t+h} is

$\hat{y}_{t+h} = n^{-1}\sum_{i=1}^{n}\hat{y}^i_{t+h}$ where y^i_{t+h} is the forecast obtained with variable x_i.

- *Bayesian model averaging (BMA)*

  We start by estimating the n direct augmented autoregressions described in EWA, each representing model M_i with $i = 1, \ldots, n$. We assume a prior probability for each model equal to $P(M_i) = n^{-1}$ for $i = 1, \ldots, n$. With observed data, D, we can compute the posterior probability model i is the true model, $P(M_i/D)$, and use it to weight the n individual forecasts. More details and applications are given in Koop and Potter (2003), Wright (2009) and Faust and Wright (2009).

  We follow the assumptions in Faust and Wright (2009). We further follow Fernandez et al. (2001) in assuming that $\varepsilon^i_{t+h} \sim N(0, \sigma^2)$ and that the marginal prior of σ is proportional to $\frac{1}{\sigma}$. Further, we assume the prior of $\lambda_{i,h} = [\rho^i_{0,h} \quad \rho^i_{1,h} \ldots \rho^i_{p,h} \quad \beta_{i,h}]'$ conditional on σ is $N(\overline{\lambda}_{i,h}, \phi(\sigma^2\sum_{t=1}^{T}(w_{it}w'_{it})^{-1}))$ where $w_{it} = [1 \quad y_t \quad y_{t-1} \ldots y_{t+1-p} \quad x_{it}]'$ and $\overline{\lambda}_{i,h} = [\overline{\rho}^i_{0,h} \quad \overline{\rho}^i_{1,h} \ldots \overline{\rho}^i_{p,h} \quad \overline{\beta}_{i,h}]'$, where $\overline{\beta}_{i,h} = 0$ and $\overline{\rho}^i_{0,h}, \overline{\rho}^i_{1,h}, \ldots, \overline{\rho}^i_{p,h}$ are OLS estimates obtained in the sample 1959Q2-1984Q1 (minus h quarters). The hyperparameter ϕ sets the informativeness of the prior, with small values corresponding to more informative priors. We considered the values of ϕ delivering the best results for each series in Valle e Azevedo and Pereira (2013). Next, we take the posterior mean of $\lambda_{i,h}$, given by $\widetilde{\lambda}_{i,h} = \frac{\hat{\lambda}_{i,h}\phi}{1+\phi} + \frac{\overline{\lambda}_{i,h}\phi}{1-\phi}$, where $\hat{\lambda}_{i,h}$ are the OLS estimates of $\lambda_{i,h}$ and compute n forecasts of y_{t+h} as $\hat{y}^i_{t+h|t} = \widetilde{\lambda}'_{i,h}w_{it}$. Finally, the *BMA* forecast is given by $\hat{y}_{t+h|t} = \sum_{i=1}^{n} P(M_i/D)\hat{y}^i_{t+h|t}$.

- *Low-pass filter (LPF)*

  We use as forecast of y_{t+h}, $\widehat{y}^{Low}_{t+h|t} := \alpha_0 + \sum\limits_{j=0}^{p}\widehat{B}^p_j y_{t-j}$ the estimated solution to the problem:

$$\underset{\alpha_0, \{\widehat{B}^p_j\}_{j=0.,\ldots,p}}{Min} \quad E[(y^{Low}_{t+h} - \widehat{y}^{Low}_{t+h})^2] \tag{1}$$

  where $y^{Low}_{t+h} = B(L)y_{t+h}$ and $B(L) = \sum\limits_{j=-\infty}^{\infty} B_j L^j$ is just a low-pass filter eliminating fluctuations with period below a given cut-off period. The weights of $B(L)$ are well-known and given by:

$$B_o = \frac{\omega_h}{\pi}, \qquad B_j = \frac{\sin[\omega_h j]}{\pi j}, |j| \geq 1, \omega_h = \frac{2\pi}{\text{cut-off}}$$

Thus, this approach corresponds to predicting a smooth version of y_{t+h}, and then regarding the prediction y^{Low}_{t+h} as a forecast of y_{t+h} itself. We use the solution to problem (1) discussed in Wildi (1998) and Christiano and Fitzgerald (2003) for stationary $\{y_t\}$, see also Wildi (2008). To implement it we need to estimate the spectrum (or autocovariances of y_t). We employ a standard non-parametric estimator, where each autocovariance $\widehat{\gamma}(k)$, $k = 0, 1, ..., M(T) < T$, with T representing the sample size, is weighted by the Bartlett lag window: $\kappa(k,T) = (1 - k/(M(T) + 1))$. We avoid the choice of a particular function $M(T)$ and set simply $M = 30$. Given this we set $p = 50 - h$; more details can be found in Valle e Azevedo and Pereira (2013).[2] As for the cut-off period, we will make it vary with the forecast horizon and the variable being forecasted, see the next section.

Finally, we will always compare the various methods (incorporating or not survey nowcasts in the dataset) with SPF forecasts themselves.

3 Empirical forecast results

3.1 Data and pseudo out-of-sample design

We analyze seven representative US macroeconomic time series forecasted by the Philadelphia SPF. We cover real activity (real GDP and the unemployment rate), the housing market (residential investment and housing starts), inflation (CPI and GDP inflation) as well as a nominal risk-free rate (3-month treasury bill rate). We use the October 2013 vintage of these series available at the website of the Federal Reserve Bank of Philadelphia. The data spans from 1959Q2 (after transformations) until 2013Q3. Comparability with SPF forecasts requires aggregation of monthly data into 3 month averages. Log differences are applied to all the series except the unemployment rate and the 3-month treasury bill rate (which are in first differences). Further details can be found in the data appendix. The dataset also includes a panel of indicators (mostly monthly indicators

[2] $M = 30$ guarantees a reasonably large number of observations (a minimum of 60 observations at every horizon) for the estimation of the $\widehat{\gamma}(k)$ of large order needed at the beginning of our evaluation sample (1984Q1, see the next section). We could then make M as a function of the sample size but avoided any such choice. Given this M we must guarantee that the technical restriction $p > M$ is satisfied by the parameters of the filter. $p = 50 - h$, with h ranging from 1 to 12, guarantees this is the case, although larger values would be feasible. Nonetheless, we have verified that, given our choice of M, the estimated solution to (1) would differ little with larger values of p as very little weight is attached to the larger lags of y_t in the solution.

which are aggregated quarterly as 3 month averages) to be used in the multivariate methods; see more details in the data appendix.

Except for possible data revisions (only relevant, if at all, in the case of real GDP and residential investment), we simulate a real-time forecast with all methods, while making sure there is never an informational advantage over SPF forecasts. SPF panelists submit what we denote as h-quarters ahead forecasts of y_t (i.e., forecasts of y_{t+h}), for $h = 0, ..., 4$ in the middle of quarter t. For the other methods, we simulate a forecast that can always be constructed in the middle of quarter t. Still, we use only observations of time series referring to quarter $t-1$ and **earlier** and always released before or around the middle of quarter t. Therefore, without using SPF nowcasts as a starting point (i.e., forecasts of y_t submitted in the middle of quarter t), the other methods face a disadvantage over SPF forecasts, especially in the case of rapidly released time series such as CPI inflation or 3-month treasury bill rates.[3]

We report results for horizons (in quarters) $h = 1, 2, 4, 6, 8$ and 12. The estimation sample always starts in 1959Q2 whereas the evaluation sample starts in 1984Q1, coinciding with the start of the Great Moderation (see e.g., Giannone et al. 2008a and McConnel and Perez-Quiros 2000) and ends in 2013Q3. In the forecast comparisons below we highlight the impact of treating SPF nowcasts as an additional observation of the time series of interest.

3.2 Results

This section discusses the results, which are analyzed in terms of the root mean squared forecast error (RMSFE) of the competing forecasts. The RMSFE is presented as a ratio calculated *vis-à-vis* the RMSFE of LPF predictions **without** SPF nowcast extension. The cut-off used to compute LPF forecasts is the one that minimizes the RMSFE of the LPF without SPF nowcast extension (i.e., the benchmark) over the evaluation period, 1984Q1-2013Q3, and we report it in Table 1.[4] The general pattern is that the optimal cut-off increases slowly, or remains stable, as the forecast horizon increases. Most optimal cut-off values (say, those between 8 and 32) correspond to typical business

[3]In other words, at quarter t, the prediction for $t+1$ without nowcast is in fact a two-step-ahead forecast, since the last available data point refers to $t-1$. On the other hand, with the nowcast, the prediction for $t+1$ is a one-step-ahead forecast, as the nowcast extends the series up to t.

[4]We searched within a grid with minimum of 4 quarters (1 year) to a maximum of 48 quarters (12 years) in increments of 4 quarters while verifying that, in cases where the optimal cut-off is 48, larger values (up to 84 quarters) imply, if anything, minimal reductions in the RMSFE.

cycle frequencies; the largest values are found for the variables residential investment, housing starts and CPI inflation. This choice embodies quite obviously hindsight. Hence, it is reasonable to verify if alternative cut-offs, derived for instance in the pre-evaluation sample 1974Q1-1983Q4, resemble these. More important than this assessment is the impact of this and other sub-optimal choices of the cut-off in forecast accuracy; we postpone such analysis to subsection 3.2.2.

Table 1
Optimal cut-off period for the Low-Pass filter (without nowcast), for each variable, by forecast horizon

Variable	**Sample Period**	**Forecast Horizon**					
		1	2	4	6	8	12
Real output growth	1984Q1-2013Q3	8	12	20	20	24(4)	28
	1974Q1-1983Q4	8	8	8	20	20	20
Unemployment Rate	1984Q1-2013Q3	4	12	12	20	20	20
	1974Q1-1983Q4	4	4	4	20	20	20
Real Private Fixed Investment - Residential	1984Q1-2013Q3	8	28	28	28	28	28
	1974Q1-1983Q4	4	20	20	20	20	20
Housing Starts	1984Q1-2013Q3	28	28	28	28	28	28
	1974Q1-1983Q4	4	4	16	16	20	20
CPI Inflation	1984Q1-2013Q3	32	36	36	32	32(4)	32(12)
	1974Q1-1983Q4	8	16	20	48	48	48
GDP inflation	1984Q1-2013Q3	12	12	12	12	12	12
	1974Q1-1983Q4	8	16	40	48	48	48
3-Month T-bill rate	1984Q1-2013Q3	8	8	16	16	16	32
	1974Q1-1983Q4	4	4	4	4	20	20

Notes: each entry reports the optimal cut-off period by forecast horizon for each variable in the two sample periods considered: 1984Q1-2013Q3, which corresponds to the evaluation period, and 1974Q1-1983Q4, i.e., before de evaluation period. The optimal cut-off for each variable and forecast horizon is the cut-off minimizing the RMSFE in each sample. The estimation sample always begins in 1959Q2. The optimal cut-off is generally increasing with the forecast horizon. Readings within brackets signal cases where the computed optimal cut-off takes on local minima value, but where the option was to disregard these local minima and use the second-best cut-off period that is presented outside the brackets.

Table 2 summarizes the results by variable and forecast horizon. The first row of panel (A) reports the RMSFE by horizon obtained with the LPF predictions without SPF nowcast extension (benchmark). All other entries in panels (A) and (B) report relative RMSFEs, i.e., the ratio of the RMSFE attained with each method relative to the benchmark. We stress that in panel (A) the methods do not make use of SPF's nowcasts; in panel (B) they do. Entries below one indicate that the benchmark is outperformed. Panel (C), in turn, shows the gain in RMSFE that is attained, by each model/method, by using the nowcast. In addition, Table 3 presents the p-values of the Diebold and Mariano (1995) (DM, henceforth) test of predictive accuracy. Given the actual series and two competing sets of forecasts, the DM tests the null hypothesis of equal forecast accuracy (equal RMSFE). In panels (A) and (B) the DM evaluates the performance of each model against the LPF. While in panel (A) this is done in a no-nowcast extension scenario, in panel (B) the test is run for the forecasts obtained once the series of interest has been extended with the nowcast. In turn, panel (C) shows the p-values of the DM test applied to forecasts of the same model produced both with and without the nowcast.

The most evident takeaway from these results is that it is very difficult to draw very general conclusions. In fact, the results vary across variables both in what concerns the desirability of using one model over the other(s) and whether or not to use SPF nowcasts as the starting point (jump-off). Nevertheless, it is possible to say that the LPF shows up as a powerful method overall, and that lengthening the observed time series with SPF nowcasts enhances forecast accuracy in a significant majority of cases.

We now detail the main results. Firstly, the SPF is extremely hard to beat at very short horizons, but the results show that this advantage is diluted as the horizon increases. Given this and the fact that the SPF only forecasts up to 4 quarters ahead, the alternative methods seem to be more useful for medium-term forecasting purposes.

Secondly, apart from the SPF, the LPF shows up as the preferred method. Though some other models, namely IAR, DAR and EWA, behave often quite well, the LPF has the best overall performance. This is easily read from panels (A) and (B) in Table 2, which predominantly show ratios greater than one. In addition, the LPF outperforms the SPF in several instances. Examples include GDP inflation and residential investment.

Thirdly, using the SPF nowcast extension is generally conducive to more accurate predictions. This is not very surprising, since filling in the series with up-to-date information grants the methods an important informational bonus compared with the no-nowcast setting. The largest gains seem to be for shorter-term predictions (consistent with our first main result) and weaker methods (in particular the RW).

Table 2

Relative RMSFEs by variable and forecast horizon. Evaluation period: 1984Q1-2013Q3

	(A) Without the nowcast						*(B) With the nowcast*						*(C) Percent gain in RMSFE vs. nowcast*					
	Forecast horizon						Forecast horizon						Forecast horizon					
Model	1	2	4	6	8	12	1	2	4	6	8	12	1	2	4	6	8	12
Real output growth																		
LPF (RMSFE)	0.5772	0.6116	0.6272	0.6387	0.6495	0.6855	0.97	0.98	0.99	1.00	0.99	0.99	2.54	2.44	0.88	0.25	0.52	1.42
IAR	1.00	1.01	1.00	0.99	0.97	0.92	0.98	0.97	0.99	0.99	0.97	0.92	2.44	3.32	0.86	-0.02	-0.02	-0.06
DAR	1.01	1.01	1.02	1.01	0.97	0.92	0.99	0.98	1.00	1.00	0.99	0.93	2.05	3.81	2.23	1.31	-1.73	-0.27
RW	1.16	1.27	1.35	1.35	1.40	1.42	1.04	1.00	1.08	1.17	1.20	1.20	10.54	21.19	19.52	13.05	14.52	15.60
EWA	1.01	1.02	1.05	1.01	0.97	0.94	0.98	0.98	1.03	1.01	0.97	0.96	3.50	4.65	1.96	-0.39	-0.42	-1.35
BMA	1.05	1.09	1.12	1.03	1.13	1.00	1.00	1.03	1.09	1.04	1.14	1.02	4.51	6.04	1.93	-1.52	-0.36	-1.64
FAVAR	1.16	1.09	1.08	1.03	1.00	0.95	1.11	1.05	1.08	1.03	1.00	0.95	3.95	3.60	0.25	-0.03	-0.23	-0.04
DFAAR	1.06	1.08	1.07	1.05	0.98	0.94	1.03	1.02	1.04	1.04	0.99	0.94	3.55	4.81	2.87	0.62	-1.71	-0.04
SPF	0.95	0.97	1.00	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Unemployment rate																		
LPF (RMSFE)	0.2487	0.2609	0.2805	0.2763	0.2744	0.2766	1.00	1.00	1.01	1.01	1.00	1.00	-0.10	0.25	-1.01	-0.61	-0.27	-0.08
IAR	1.01	1.08	1.08	1.06	1.06	1.05	1.01	1.06	1.08	1.06	1.06	1.05	0.44	1.36	-0.41	0.24	0.20	-0.09
DAR	1.01	1.07	1.05	1.03	1.03	1.04	1.00	1.06	1.06	1.04	1.04	1.04	1.04	1.43	-0.71	-0.77	-1.34	0.32
RW	1.09	1.21	1.42	1.57	1.74	1.68	1.01	1.09	1.25	1.36	1.49	1.47	7.45	9.60	12.48	13.33	14.38	12.53
EWA	1.00	1.06	1.03	1.01	1.03	1.04	1.01	1.05	1.06	1.02	1.03	1.04	-0.90	0.43	-2.56	-0.39	-0.65	0.09
BMA	1.12	1.07	1.07	1.02	1.03	1.02	1.04	1.08	1.10	1.02	1.03	1.02	6.63	-0.37	-2.97	-0.44	0.03	0.04
FAVAR	1.00	1.03	0.99	1.03	1.04	1.06	0.99	1.03	0.99	1.03	1.04	1.06	1.48	0.50	-0.75	-0.28	-0.06	-0.26
DFAAR	0.99	1.08	1.08	1.05	1.02	1.01	1.00	1.04	1.08	1.05	1.05	1.02	-1.50	3.28	0.38	0.36	-2.12	-0.76
SPF	0.98	0.95	0.96	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Real private Res. fixed Inv.																		
LPF (RMSFE)	3.0414	3.0700	3.1449	3.1985	3.2108	3.2186	0.97	1.00	1.00	1.00	1.00	1.00	2.88	0.46	-0.15	0.03	-0.08	-0.27
IAR	1.03	1.10	1.14	1.10	1.08	1.09	1.00	1.08	1.14	1.10	1.08	1.09	3.24	2.06	0.06	-0.07	-0.05	0.11
DAR	1.02	1.09	1.11	1.13	1.21	1.10	0.99	1.05	1.11	1.09	1.16	1.12	2.68	3.33	0.54	3.55	3.82	-1.43
RW	1.13	1.23	1.39	1.47	1.56	1.75	0.95	1.00	1.08	1.15	1.17	1.29	15.70	19.23	22.12	21.58	24.91	26.16
EWA	0.99	1.06	1.14	1.15	1.21	1.12	0.97	1.04	1.12	1.11	1.16	1.12	1.36	1.56	2.01	2.95	3.97	-0.32
BMA	1.00	1.08	1.16	1.15	1.25	1.10	0.98	1.07	1.14	1.09	1.16	1.11	2.13	0.93	1.74	5.71	6.79	-0.68
FAVAR	1.16	1.21	1.21	1.12	1.10	1.10	1.02	1.11	1.21	1.15	1.10	1.09	12.06	8.49	-0.06	-2.29	-0.42	0.72
DFAAR	1.04	1.10	1.15	1.15	1.08	1.12	0.96	1.08	1.17	1.14	1.11	1.11	8.01	1.90	-1.73	0.91	-2.36	0.85
SPF	0.93	1.02	1.08	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-

(continued)

Model	(A) Without the nowcast						(B) With the nowcast						(C) Percent gain in RMSFE vs. nowcast					
	Forecast horizon						Forecast horizon						Forecast horizon					
	1	2	4	6	8	12	1	2	4	6	8	12	1	2	4	6	8	12
Housing starts																		
LPF (RMSFE)	6.8114	6.8369	6.8335	6.8281	6.8530	6.8271	0.99	0.99	1.00	1.00	1.00	1.00	1.19	0.88	0.19	0.06	0.11	-0.22
IAR	1.05	1.06	1.05	1.03	1.03	1.04	1.03	1.04	1.05	1.04	1.03	1.04	2.23	1.52	-0.50	-0.09	0.06	0.09
DAR	1.05	1.05	1.04	1.06	1.08	1.04	1.03	1.03	1.04	1.04	1.08	1.04	1.71	1.40	-0.20	1.55	-0.32	0.23
RW	1.32	1.34	1.37	1.41	1.45	1.61	1.06	1.07	1.13	1.19	1.16	1.17	19.92	20.27	17.21	15.75	20.10	27.72
EWA	1.04	1.06	1.05	1.07	1.09	1.02	1.03	1.03	1.05	1.05	1.08	1.05	1.06	2.41	0.07	1.97	0.59	-2.01
BMA	1.05	1.08	1.02	1.05	1.09	1.02	1.03	1.05	1.02	1.02	1.07	1.04	2.06	2.33	0.43	3.08	1.28	-2.01
FAVAR	1.08	1.09	1.08	1.05	1.04	1.04	1.06	1.08	1.09	1.06	1.04	1.04	2.39	0.91	-1.15	-0.51	-0.30	0.06
DFAAR	1.06	1.09	1.04	1.07	1.04	1.05	1.04	1.05	1.06	1.08	1.03	1.04	2.31	3.10	-2.37	-1.39	0.75	1.10
SPF	1.00	1.10	1.10	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
CPI inflation																		
LPF (RMSFE)	0.5127	0.5062	0.5052	0.5249	0.5423	0.5400	0.95	0.99	0.99	0.95	0.94	0.97	4.72	0.75	1.42	4.98	6.00	2.60
IAR	1.14	1.17	1.10	1.11	1.12	1.16	1.01	1.12	1.06	1.04	1.06	1.14	11.19	3.63	3.78	6.16	5.53	1.84
DAR	1.12	1.18	1.18	1.13	1.14	1.42	1.01	1.11	1.09	1.04	1.07	1.34	9.55	6.03	7.38	7.67	5.59	5.38
RW	1.31	1.29	1.30	1.28	1.31	1.32	1.01	1.10	1.10	1.05	1.01	1.14	23.11	15.16	15.07	18.59	23.09	13.98
EWA	1.14	1.17	1.16	1.13	1.12	1.39	1.02	1.12	1.07	1.08	1.10	1.32	10.40	3.91	7.36	3.98	2.20	5.55
BMA	1.22	1.25	1.29	1.24	1.20	1.57	1.02	1.19	1.17	1.17	1.17	1.52	15.89	4.41	9.29	5.91	2.84	2.79
FAVAR	1.19	1.21	1.12	1.09	1.12	1.17	1.01	1.11	1.05	1.04	1.05	1.12	15.06	8.13	6.35	4.71	6.21	4.28
DFAAR	1.21	1.23	1.19	1.25	1.18	1.23	1.03	1.16	1.12	1.12	1.13	1.24	15.10	5.62	5.68	10.60	4.28	-0.62
SPF	0.89	0.94	0.95	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
GDP inflation																		
LPF (RMSFE)	0.1906	0.2080	0.2320	0.2483	0.2571	0.2881	0.97	0.99	0.98	0.96	0.95	0.93	3.34	0.72	2.32	3.58	5.06	7.26
IAR	1.07	1.10	1.19	1.29	1.40	1.64	1.11	1.13	1.21	1.31	1.41	1.60	-4.14	-3.21	-2.05	-1.72	-0.44	2.05
DAR	1.07	1.09	1.22	1.35	1.52	1.88	1.12	1.14	1.28	1.38	1.53	1.88	-4.19	-3.94	-4.64	-2.10	-0.92	0.10
RW	1.13	1.13	1.17	1.21	1.29	1.53	1.15	1.17	1.17	1.21	1.26	1.44	-1.46	-3.62	0.28	-0.24	2.34	6.15
EWA	1.03	1.06	1.19	1.33	1.47	1.86	1.08	1.10	1.22	1.33	1.44	1.82	-5.44	-3.40	-2.61	-0.16	2.30	2.45
BMA	1.07	1.02	1.68	1.99	1.70	2.01	1.08	1.06	1.49	1.80	1.65	1.99	-1.04	-3.36	11.25	9.86	3.02	0.70
FAVAR	1.22	1.27	1.37	1.43	1.54	1.66	1.15	1.26	1.34	1.39	1.47	1.56	6.03	0.70	1.87	2.68	4.12	6.01
DFAAR	1.02	1.16	1.35	1.46	1.52	1.75	1.08	1.15	1.33	1.41	1.49	1.68	-6.27	0.79	0.93	3.54	2.19	3.94
SPF	1.19	1.21	1.24	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-

(continued)

Model	(A) *Without the nowcast* Forecast horizon 1	2	4	6	8	12	(B) *With the nowcast* Forecast horizon 1	2	4	6	8	12	(C) *Percent gain in RMSFE vs. nowcast* Forecast horizon 1	2	4	6	8	12
3-Month treasury bill rate																		
LPF (RMSFE)	0.4355	0.4571	0.4645	0.4630	0.4620	0.4573	0.94	0.97	1.00	1.00	1.00	1.00	6.45	3.09	0.08	-0.21	-0.17	0.19
IAR	1.15	1.00	1.01	1.02	1.00	1.02	1.05	1.06	1.00	1.02	1.00	1.02	8.73	-6.84	1.16	-0.16	-0.21	-0.49
DAR	1.20	0.99	1.03	1.03	1.16	1.03	1.04	1.10	1.02	1.03	1.13	1.06	13.30	-11.09	0.88	0.52	2.54	-2.76
RW	1.21	1.23	1.43	1.71	1.76	1.86	1.00	1.12	1.26	1.45	1.57	1.58	16.81	9.24	11.95	14.88	11.14	14.94
EWA	1.19	1.00	1.03	1.10	1.12	1.08	1.05	1.09	1.02	1.03	1.07	1.11	12.07	-9.43	0.89	5.87	4.72	-2.07
BMA	1.22	1.00	1.05	1.13	1.14	1.08	1.08	1.11	1.04	1.06	1.10	1.10	11.76	-10.98	1.58	6.14	3.45	-1.73
FAVAR	1.24	1.01	1.02	1.02	1.01	1.02	1.14	1.12	1.00	1.01	1.00	1.01	8.35	-11.59	1.81	0.74	0.54	1.38
DFAAR	1.15	0.99	1.03	1.06	1.07	1.05	1.10	1.08	1.03	1.06	1.02	1.05	4.25	-9.37	0.45	-0.30	4.87	-0.32
SPF	0.95	1.03	1.05	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-

Notes: The first line of panel (A) reports the RMSFE by horizon obtained with the low-pass filter (LPF) without the nowcast (benchmark). All other entries in panels (A) and (B) report relative RMSFEs, i.e., the ratio of the RMSFE of each method's forecasts relative to the benchmark. Note that, in panel (A), the methods do not make use of SPF's nowcasts, while in panel (B) they do. Entries below one denote that the benchmark is outperformed. Panel (C), in turn, shows the gain in RMSFE that is attained by using the nowcast. For each model/method i, this is calculated as $[1-(RMSFE_{NowcastModel_i}/RMSFE_{Model_i})]\times 100$. Cases where the nowcast results in poorer performance are shaded. The estimation sample always starts in 1959Q2. The evaluation period is 1984Q1-2013Q3, spanning from the beginning of the Great Moderation to the end of our dataset. The exceptions are 12-quarter horizon forecasts for CPI inflation, 3-Month treasury bill rate and Real private Residential fixed Investment, to which the applicable evaluation period is 1984Q3-2013Q3. These exceptions are justified by the fact the first SPF release of these variables happened only in 1981Q3, whilst the survey dates back to 1968Q4. Since the SPF nowcast is taken as the last available observation of the nowcast-augmented series, this implies that the first feasible 12-quarter horizon forecast for these variables refers to 1984Q3 (12 quarters after 1981Q3), pushing the evaluation period 2 quarters forward. Though this issue is relevant only when the nowcast is being used, the corresponding no-nowcast cases share this reduced evaluation period with the purpose of ensuring the comparability of predictions.

Table 3

p-values of Diebold and Mariano test of equal predictive accuracy. Evaluation period: 1984Q1-2013Q3

	(A) Without nowcast; benchmark is LPF						*(B) With nowcast; benchmark is LPF*						*(C) Each model with vs. without nowcast*					
	Forecast horizon						Forecast horizon						Forecast horizon					
Model	1	2	4	6	8	12	1	2	4	6	8	12	1	2	4	6	8	12
Real output growth																		
LPF (RMSFE)	-	-	-	-	-	-	-	-	-	-	-	-	0.38	0.03	0.30	0.83	0.53	0.08
IAR	0.98	0.83	0.99	0.85	0.75	0.47	0.95	0.89	0.98	0.86	0.77	0.52	0.35	0.04	0.03	0.83	0.88	0.61
DAR	0.85	0.63	0.74	0.88	0.79	0.51	0.71	0.98	0.88	0.97	0.95	0.59	0.46	0.02	0.08	0.15	**0.08**	0.74
RW	0.01	0.00	0.00	0.00	0.03	0.00	0.14	0.33	0.03	0.02	0.02	0.07	0.23	0.00	0.00	0.00	0.12	0.00
EWA	0.65	0.44	0.50	0.94	0.78	0.63	0.88	0.94	0.51	0.88	0.83	0.80	0.20	0.01	0.19	0.39	0.65	0.39
BMA	0.21	0.06	0.25	0.81	0.43	1.00	0.47	0.13	0.20	0.67	0.34	0.81	0.13	0.01	0.25	**0.09**	0.89	0.25
FAVAR	0.00	0.01	0.33	0.80	0.99	0.62	0.01	0.05	0.26	0.74	0.96	0.70	0.00	0.00	0.22	0.91	**0.07**	0.89
DFAAR	0.14	0.07	0.41	0.64	0.82	0.59	0.26	0.11	0.48	0.62	0.99	0.67	0.09	0.05	0.06	0.47	0.34	0.96
SPF	0.40	0.58	0.93	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Unemployment rate																		
LPF (RMSFE)	-	-	-	-	-	-	-	-	-	-	-	-	0.97	0.87	0.28	0.17	**0.06**	0.75
IAR	0.48	0.00	0.01	0.07	0.15	0.15	0.63	0.00	0.01	0.07	0.17	0.19	0.87	0.39	0.30	0.52	0.47	0.69
DAR	0.77	0.01	0.03	0.29	0.47	0.07	0.79	0.03	0.06	0.23	0.33	0.07	0.65	0.44	0.17	**0.00**	**0.09**	0.67
RW	0.06	0.01	0.03	0.02	0.01	0.00	0.75	0.18	0.08	0.03	0.02	0.01	0.08	0.02	0.02	0.03	0.01	0.01
EWA	0.86	0.01	0.26	0.73	0.01	0.16	0.82	0.03	0.16	0.76	0.16	0.12	0.75	0.83	**0.03**	-0.36	-0.60	0.80
BMA	0.10	0.05	0.26	0.70	0.04	0.45	0.33	0.05	0.09	0.72	0.09	0.38	0.00	0.87	**0.02**	0.50	0.98	0.95
FAVAR	1.00	0.22	0.79	0.64	0.49	0.21	0.47	0.20	0.75	0.67	0.50	0.20	0.59	0.84	0.35	0.34	0.76	0.12
DFAAR	0.71	0.02	0.18	0.50	0.68	0.65	0.93	0.13	0.14	0.57	0.43	0.33	0.83	0.51	0.77	0.54	**0.01**	0.41
SPF	0.16	0.15	0.31	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Real private Res. fixed Inv.																		
LPF (RMSFE)	-	-	-	-	-	-	-	-	-	-	-	-	0.19	0.34	0.67	0.84	0.43	0.26
IAR	0.34	0.15	0.12	0.10	0.06	0.07	0.26	0.13	0.13	0.11	0.07	0.07	0.31	0.30	0.00	0.71	0.57	0.05
DAR	0.44	0.17	0.14	0.12	0.10	0.10	0.25	0.11	0.14	0.12	0.04	0.07	0.29	0.29	0.38	0.15	0.47	0.24
RW	0.09	0.04	0.04	0.01	0.01	0.00	0.57	1.00	0.35	0.02	0.00	0.04	0.01	0.01	0.04	0.01	0.02	0.00
EWA	0.59	0.28	0.11	0.09	0.09	0.10	0.92	0.30	0.17	0.14	0.06	0.08	0.47	0.26	0.00	0.09	0.38	0.85
BMA	0.97	0.20	0.16	0.05	0.08	0.10	0.81	0.21	0.19	0.05	0.15	0.09	0.29	0.47	0.04	0.09	0.15	0.73
FAVAR	0.03	0.08	0.16	0.18	0.04	0.06	0.23	0.11	0.14	0.21	0.10	0.09	0.02	0.05	0.96	0.33	0.76	0.46
DFAAR	0.26	0.23	0.13	0.16	0.11	0.10	0.62	0.23	0.13	0.16	0.12	0.09	0.04	0.35	**0.06**	0.16	0.16	0.64
SPF	0.22	0.31	0.13	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-

(continued)

Model	(A) *Without nowcast; benchmark is LPF*						(B) *With nowcast; benchmark is LPF*						(C) *Each model with vs. without nowcast*					
	Forecast horizon						Forecast horizon						Forecast horizon					
	1	2	4	6	8	12	1	2	4	6	8	12	1	2	4	6	8	12
Housing starts																		
LPF (RMSFE)	-	-	-	-	-	-	-	-	-	-	-	-	0.16	0.19	0.67	0.76	0.37	0.17
IAR	0.00	0.01	0.02	0.08	0.05	0.04	0.00	0.00	0.03	0.09	0.06	0.04	0.33	0.43	0.23	0.36	0.32	0.16
DAR	0.00	0.00	0.10	0.02	0.00	0.05	0.00	0.02	0.05	0.15	0.04	0.00	0.37	0.44	**0.03**	0.04	0.79	0.86
RW	0.00	0.00	0.00	0.00	0.00	0.00	0.14	0.09	0.03	0.00	0.00	0.06	0.00	0.01	0.07	**0.02**	0.02	0.00
EWA	0.00	0.08	0.12	0.01	0.01	0.07	0.00	0.00	0.13	0.16	0.01	0.05	0.60	0.34	0.94	0.05	0.69	0.27
BMA	0.00	0.06	0.30	0.03	0.01	0.08	0.00	0.01	0.40	0.38	0.02	0.06	0.39	0.31	0.66	0.00	0.33	0.27
FAVAR	0.00	0.09	0.09	0.14	0.03	0.03	0.01	0.06	0.07	0.15	0.03	0.04	0.05	0.38	0.31	0.38	0.33	0.87
DFAAR	0.05	0.13	0.08	0.07	0.03	0.08	0.00	0.13	0.09	0.15	0.12	0.02	0.29	0.13	0.12	0.55	0.38	0.47
SPF	0.91	0.11	0.21	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
CPI inflation																		
LPF (RMSFE)	-	-	-	-	-	-	-	-	-	-	-	-	0.05	0.52	0.00	0.02	0.00	0.00
IAR	0.14	0.12	0.00	0.00	0.00	0.13	0.28	0.17	0.00	0.00	0.00	0.07	0.06	0.02	0.03	0.04	0.00	0.33
DAR	0.14	0.14	0.00	0.01	0.00	0.10	0.28	0.17	0.00	0.00	0.01	0.06	0.04	0.06	0.01	0.10	0.01	0.23
RW	0.09	0.16	0.00	0.09	0.05	0.04	0.15	0.16	0.04	0.02	0.06	0.06	0.08	0.14	0.00	0.10	0.04	0.12
EWA	0.17	0.12	0.01	0.02	0.02	0.13	0.30	0.16	0.01	0.00	0.00	0.08	0.06	0.04	0.05	0.07	0.01	0.26
BMA	0.16	0.13	0.02	0.00	0.00	0.01	0.29	0.16	0.01	0.00	0.00	0.00	0.10	0.03	0.06	0.02	0.04	0.18
FAVAR	0.17	0.19	0.00	0.07	0.01	0.12	0.19	0.17	0.12	0.00	0.01	0.08	0.14	0.17	0.00	0.06	0.00	0.02
DFAAR	0.21	0.15	0.04	0.06	0.02	0.08	0.13	0.17	0.02	0.03	0.00	0.03	0.21	0.09	0.09	0.08	0.26	0.56
SPF	0.09	0.12	0.10	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
GDP inflation																		
LPF (RMSFE)	-	-	-	-	-	-	-	-	-	-	-	-	0.61	0.90	0.79	0.60	0.33	0.03
IAR	0.00	0.00	0.00	0.01	0.03	0.13	0.01	0.03	0.02	0.02	0.02	0.09	0.53	0.40	0.46	0.61	0.90	0.52
DAR	0.00	0.00	0.00	0.01	0.02	0.11	0.01	0.03	0.01	0.01	0.02	0.10	0.53	0.38	**0.08**	0.61	0.79	0.91
RW	0.00	0.00	0.00	0.00	0.01	0.19	0.00	0.00	0.00	0.00	0.02	0.20	0.88	0.62	0.97	0.97	0.74	0.25
EWA	0.27	0.00	0.00	0.01	0.03	0.13	0.07	0.10	0.04	0.02	0.02	0.12	0.41	0.40	0.44	0.96	0.42	0.00
BMA	0.01	0.52	0.06	0.07	0.00	0.04	0.11	0.32	0.05	0.03	0.00	0.03	0.87	0.27	0.23	0.27	0.09	0.55
FAVAR	0.00	0.00	0.00	0.00	0.00	0.04	0.03	0.00	0.01	0.00	0.00	0.03	0.10	0.80	0.15	0.28	0.09	0.02
DFAAR	0.55	0.01	0.02	0.00	0.00	0.11	0.10	0.04	0.02	0.01	0.00	0.06	0.38	0.90	0.87	0.41	0.59	0.39
SPF	0.10	0.11	0.13	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-

(continued)

Model	(A) *Without nowcast; benchmark is LPF*						(B) *With nowcast; benchmark is LPF*						(C) *Each model with vs. without nowcast*					
	Forecast horizon						Forecast horizon						Forecast horizon					
	1	2	4	6	8	12	1	2	4	6	8	12	1	2	4	6	8	12
3-Month treasury bill rate																		
LPF (RMSFE)	-	-	-	-	-	-	-	-	-	-	-	-	0.00	0.00	0.87	0.49	0.58	0.60
IAR	0.00	0.87	0.84	0.70	0.99	0.53	0.00	0.00	0.98	0.71	0.99	0.50	0.00	**0.00**	0.14	0.47	0.55	0.35
DAR	0.00	0.71	0.62	0.49	0.07	0.44	0.00	0.00	0.71	0.60	0.03	0.42	0.00	0.00	0.38	0.19	0.23	0.39
RW	0.00	0.00	0.00	0.00	0.00	0.00	0.25	0.01	0.00	0.00	0.00	0.00	0.04	0.00	0.05	0.04	0.02	0.06
EWA	0.00	0.99	0.59	0.04	0.12	0.47	0.00	0.00	0.66	0.54	0.02	0.39	0.00	**0.00**	0.33	0.36	0.25	0.12
BMA	0.00	0.97	0.34	0.01	0.04	0.43	0.00	0.00	0.39	0.10	0.04	0.25	0.00	**0.00**	0.20	0.29	0.04	0.36
FAVAR	0.11	0.91	0.71	0.63	0.81	0.53	0.04	0.08	0.99	0.82	0.96	0.76	0.03	**0.02**	0.50	0.33	0.41	0.13
DFAAR	0.03	0.78	0.28	0.08	0.14	0.41	0.01	0.05	0.36	0.08	0.87	0.45	0.00	**0.00**	0.05	0.39	0.25	0.70
SPF	0.36	0.41	0.47	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-

Notes: Each entry shows, by horizon, the p-value of the Diebold-Mariano test of predictive accuracy. The loss criterion is the mean squared error. The maximum lag order used in calculating the long-run variance of the difference series from its autocovariance function is calculated from the Schwert criterion according to the sample size. Whenever this fails to deliver a positive definite autocovariance matrix (since the test is conducted using the uniform kernel), the criterion was to add or subtract one lag in order to render the computation feasible. This was necessary for: GDP inflation, panel (A), forecast horizon 2, models IAR and EWA; 3-Month treasury bill rate, panel (C), forecast horizon 1, DFAAR; Housing starts, panel (A), forecast horizon 1, models IAR, DAR and EWA, plus panel (B), forecast horizon 1, models IAR, DAR (same for forecast horizon 2), EWA and BMA. In panels (A) and (B), predictive accuracy is measured against the LPF. While in panel (A) each method without the nowcast is evaluated relative to the LPF without the nowcast, in panel (B) that assessment is made when both the competing method and the LPF already include the nowcast. This provides for a somewhat different reading than the previous table. Recall that in Table 2 both panels (A) and (B) had the same benchmark (LPF without the nowcast). It is important to contrast this, since the tables look very similar. In panel (C), the performance of each model with and without the nowcast is compared. The shaded entries denote the cases where the nowcast deteriorates model performance (these correspond to the shaded negative values in Table 2). The bold entries signal that such deterioration is statistically significant at the 10% level.

Focusing on individual variables, the frequency with which the nowcast extension improves accuracy varies substantially. The same applies to the average accuracy gain from this approach: across models, and depending on the variable and horizon studied, it may range, conditional on being positive, from about 1% to over 13% (Table 4). However, and similarly to what happens with SFP forecasts themselves, the positive impact of the nowcast generally fades away as the horizon increases. Overall, the nowcast improves the performance in 67% of all observed cases (all variables and forecast horizons), of which 46% are statistically significant at the 10% level (around 32% for all observations).

At the same time, the nowcast may have an occasional detrimental impact on accuracy (take, for instance, the forecast for the 3-month treasury bill rate at a 2-quarter horizon). Still, taken as a whole, such an effect proves to be in general statistically insignificant at conventional levels; it is significant only in 5% of all observed cases (panel (C) in Table 3). All this means that incorporating the nowcast generally enhances model forecast performance while in cases it does not, the detrimental impact is not relevant.

Table 4

Summary of forecast accuracy gains with the nowcast

Variable	Frequency (% models) w/ which nowcast improves forecast accuracy (RMSFE) — Horizon 1	2	4	6	8	12	Average accuracy gain (RMSFE) from the nowcast (across models) (%) — Horizon 1	2	4	6	8	12
Real Output growth	100	100	100	50	25	25	4.1	6.2	3.8	1.7	1.3	1.7
Unemployment rate	62.5	87.5	25.0	37.5	37.5	50	1.8	2.1	0.6	1.4	1.3	1.5
Real Private Fixed Invest. Res.	100	100	62.5	75	50	50	6	4.7	3.1	4.0	4.6	3.1
Housing Starts	100	100	50	62.5	75	62.5	4.1	4.1	1.7	2.6	2.8	3.1
CPI inflation	100	100	100	100	100	87.5	13.1	6.0	7.0	7.8	7.0	4.5
GDP inflation	25	37.5	62.5	50	75	100	-1.6	-1.9	0.9	1.9	2.2	3.6
3-month T-bill rate	100	25	100	62.5	75	37.5	10.2	-5.9	2.4	3.4	3.4	1.1

Notes: the average frequency with which the nowcast leads to lower RMSFE, by horizon, is measured as number of methods with lower RMSFE when nowcast is used divided by the total number of methods included in the paper. The methods included in the paper are: LPF, IAR, DAR, RW, EWA, BMA, FAVAR and DFAAR. By comparing their RMSFEs with and without the nowcast, it is possible to assess how the nowcast impacts model behavior by horizon. Explicitly, an entry reading of 25% means that, for that horizon, 2 out of 8 methods are improved by using the nowcast. In turn, the percentage accuracy gain quantifies the average improvement (or deterioration) in model performance that is achieved through the nowcast. This is computed as $100\sum_i$(1-(RMSFE(with nowcast)$_i$/ RMSFE(without nowcast)$_i$)/8, since the paper considers 8 alternative forecast methods. Therefore, a reading of 4.1% means that, on average, for the methods included in the paper, using the nowcast results in a 4.1% reduction in RMSFE.

3.2.1 Robustness: Sample Period

The previous subsection focused on the relative RMSFE, providing an account of the performance of the models over the entire evaluation sample. However, it is important to understand that the preceding results may be subject to some variability over time, which calls for a more detailed intra-sample analysis. This subsection tackles the issue while still emphasizing the role of the nowcast in the forecasting exercise.

Figures 1 and 2 plot the differences between the accumulated squared forecast errors obtained for each method with and without the nowcast in horizons 1 and 4, respectively. The differences are computed so that positive values indicate a better performance of the nowcast-augmented methods, with each point reading the accumulated squared error difference from 1984Q1 until the date in the x-axis. As such, we want to assess how the nowcast extension affects the models over time. Despite the fact that the SPF may provide the most accurate forecasts, we abstract from those. Rather, the focus is on assessing the impact of this approach on the statistical methods covered in the paper.

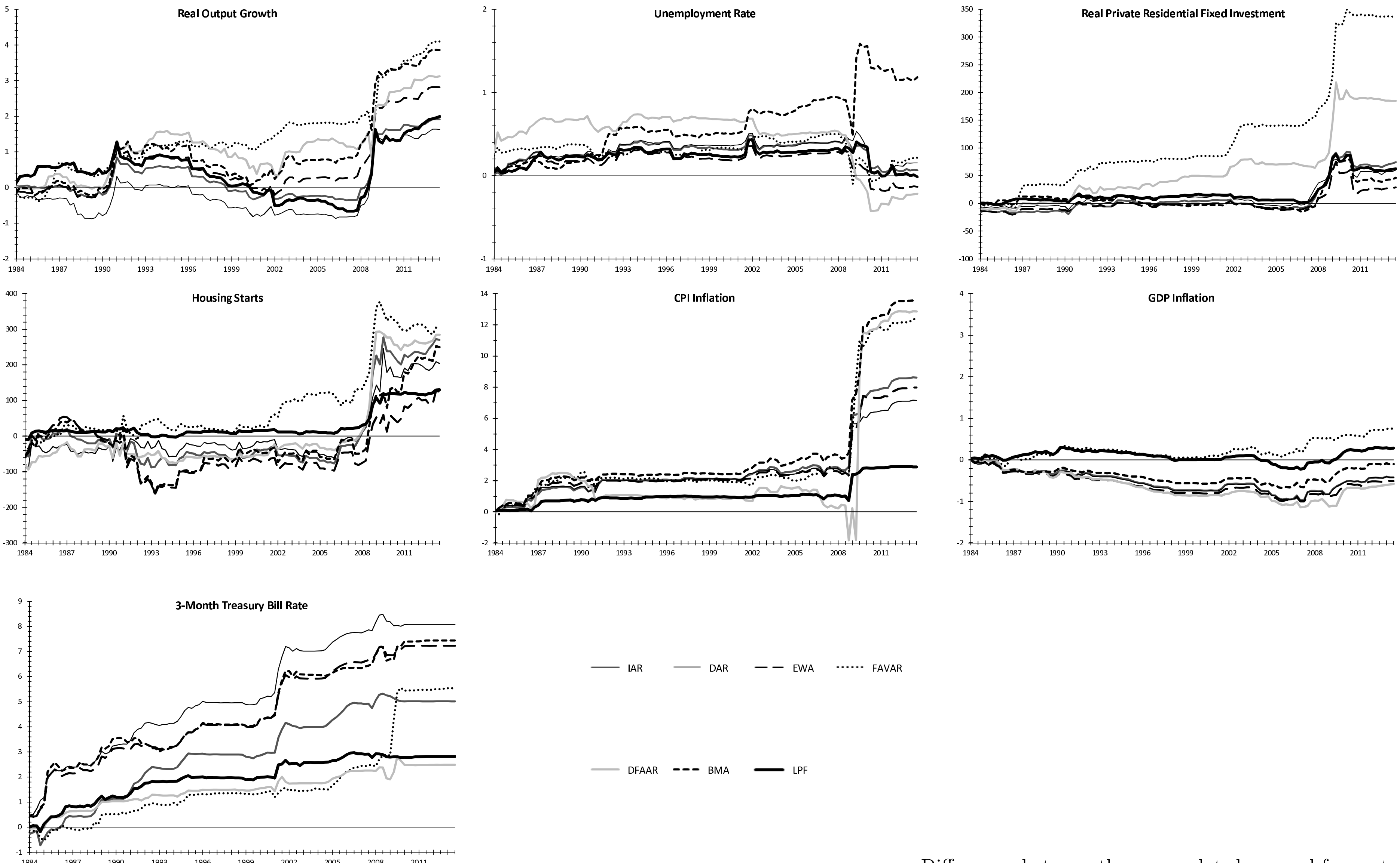
A general result is the persistence of significant differences between variables. Also worth noticing is the fact that there seems to be a greater instability in performance towards the end of the sample. Indeed, and not so surprisingly, whether or not to use the nowcast becomes more relevant in times of increased economic uncertainty, such as the the 2008 financial crisis. But, apart from that, the results seem to be quite robust along the entire evaluation sample.

Another relevant result, which can also be read from the tables in the previous subsection, is that the benefits of using the nowcast are diluted with the forecast horizon. Take for instance the 3-month treasury bill rate: whereas for $h = 1$ (Figure 1) it is straightforward to conclude that nowcast-extended forecasts fare better, for $h = 4$ (Figure 2) it becomes harder to make such a point. Nonetheless, for most variables, it is worth producing forecasts in this way. This result is especially true for CPI forecasts.

Regarding the behavior of the different methods, it is easy to spot that the biggest improvements are absorbed by the weakest methods. Still, even for the most powerful, i.e., the LPF, this approach delivers some gains in performance (note how the thicker lines in the graphs are usually above 0).

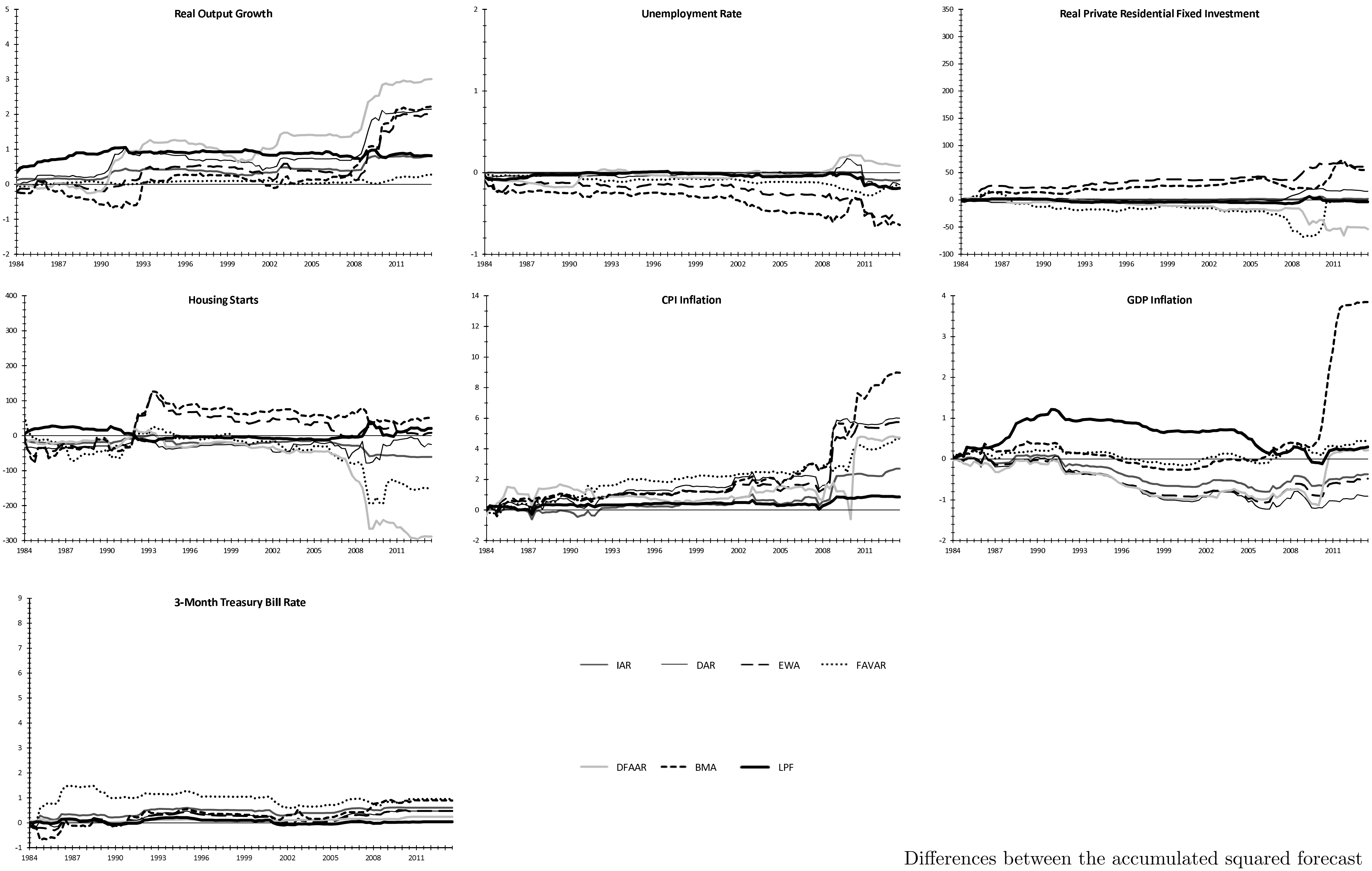
Overall, the results from this analysis confirm that naively incorporating SPF forecasts into model-based predictions adds some value to the forecasting exercise. Despite the occasional loss in performance, forecast gains usually tilt the balance in favor of this approach.

Figure 1
Difference of Accumulated Squared Forecast Errors, h=1



Differences between the accumulated squared forecast errors using each of the competing methods without the nowcast (from 1984Q1 until the date in the x-axis) and the accumulated squared forecast errors obtained with the nowcast, for each method. Evaluation sample: 1984Q1-2013Q3. The *RW* model is not displayed, as it often presents an extreme behavior hindering the correct reading of the results for the remaining methods.

Figure 2
Difference of Accumulated Squared Forecast Errors, h=4



Differences between the accumulated squared forecast errors using each of the competing methods without the nowcast (from 1984Q1 until the date in the x-axis) and the accumulated squared forecast errors obtained with the nowcast, for each method. Evaluation sample: 1984Q1-2013Q3. The *RW* model is not displayed, as it often presents an extreme behavior hindering the correct reading of the results for the remaining methods.

3.2.2 Robustness: LPF cut-off period

The cut-off period defining low and high frequencies is a critical design feature of the LPF. Hence, it is important to assess the robustness of the previous results to different choices of this parameter.

Table 5 shows the RMSFE ratios of the nowcast-augmented LPF relative to that same model without the nowcast. Given that the denominator in this ratio is based on the optimal cut-offs for the sample 1984Q1-2013Q3, the values for each variable are necessarily greater than or equal to the values in the first row (exactly equal when the optimal cut-off period coincides). Five distinct cut-off period choices are considered:

(i) Firstly, the optimal cut-off in the period 1984Q1-2013Q3 (evaluation period). This is determined by letting the cut-off vary from 4 to 48 quarters, in increments of 4, and choosing the cut-off minimizing the RMSFE in the evaluation sample. For each variable, the first line of Table 5 is therefore exactly the same as the first line of Table 2 panel (B).

(ii) Secondly, given that in (i) the choice of the cut-off is made with hindsight, we determine the cut-off in the same way but in a different sub-sample: 1974Q1-1983Q4, i.e., with data available before the benchmark evaluation period.

(iii) Finally, three other possible cut-offs are chosen for robustness purposes: 8, 16 and 32 quarters.

RMSFE ratios do change somewhat according to the choice of the cut-off period. In some cases, moving considerably away from the optimal cut-off may imply losing the lead. An example would be the unemployment rate for $h = 1$: moving away from the optimal cut-off of 4 to the robustness check cut-off of 32 would render the LPF useless compared with the other models. Nevertheless, most often the ratios vary within a very contained range (at most about 0.1), suggesting that the previous result of LPF superiority *vis-à-vis* the remaining models is not necessarily compromised. Indeed, overall the LPF continues to attain lower RMSFE ratios irrespective of the choice of the cut-off, showing that our results are robust to small variations in this important parameter.

Table 5

RMSFE obtained with different LPF cut-off choices, always with the nowcast, relative to the RMSFE obtained with the optimal cut-off in the sample 1984Q1-2013Q3 without the nowcast. Estimation sample always begins in 1959Q2.

		Forecast horizon					
Variable	**Cut-off used:**	1	2	4	6	8	12
Real output growth	optimal in sample period 1984Q1-2013Q3	0.97	0.98	0.99	1.00	0.99	0.99
	optimal in sample period 1974Q1-1983Q4	0.97	0.98	1.02	1.00	1.00	0.99
	8	0.97	0.98	1.02	1.00	0.99	1.00
	16	0.99	0.97	1.00	1.00	1.00	1.00
	32	1.03	1.00	1.01	1.01	1.01	0.99
Unemployment rate	optimal in sample period 1984Q1-2013Q3	1.00	1.00	1.01	1.01	1.00	1.00
	optimal in sample period 1974Q1-1983Q4	1.00	1.06	1.02	1.01	1.00	1.00
	8	0.97	1.02	1.05	1.03	1.03	1.02
	16	1.00	1.02	1.02	1.02	1.02	1.03
	32	1.11	1.09	1.06	1.07	1.06	1.02
Real private fixed investment	optimal in sample period 1984Q1-2013Q3	0.97	1.00	1.00	1.00	1.00	1.00
Residential	optimal in sample period 1974Q1-1983Q4	1.00	1.03	1.05	1.06	1.07	1.06
	8	0.97	1.05	1.13	1.10	1.07	1.06
	16	0.98	1.03	1.08	1.09	1.09	1.06
	32	1.01	1.02	1.02	1.02	1.01	1.01
Housing starts	optimal in sample period 1984Q1-2013Q3	0.99	0.99	1.00	1.00	1.00	1.00
	optimal in sample period 1974Q1-1983Q4	1.04	1.06	1.03	1.04	1.02	1.02
	8	1.01	1.03	1.05	1.04	1.02	1.03
	16	0.99	1.01	1.03	1.04	1.03	1.03
	32	1.00	1.00	1.01	1.01	1.01	1.01
CPI inflation	optimal in sample period 1984Q1-2013Q3	0.95	0.99	0.99	0.95	0.94	0.97
	optimal in sample period 1974Q1-1983Q4	1.05	1.04	1.02	0.99	0.99	1.04
	8	1.05	1.10	1.04	0.95	0.93	0.96
	16	1.00	1.04	1.03	0.97	0.95	0.96
	32	0.95	0.99	0.98	0.95	0.94	0.97
GDP inflation	optimal in sample period 1984Q1-2013Q3	0.97	0.99	0.98	0.96	0.95	0.93
	optimal in sample period 1974Q1-1983Q4	1.01	1.00	1.03	1.06	1.07	1.04
	8	1.01	1.04	1.00	0.97	0.96	0.93
	16	0.98	1.00	0.99	0.99	0.97	0.93
	32	1.03	1.02	0.99	0.99	0.99	0.94
3-Month treasury bill rate	optimal in sample period 1984Q1-2013Q3	0.94	0.97	1.00	1.00	1.00	1.00
	optimal in sample period 1974Q1-1983Q4	0.98	1.05	1.01	1.01	1.00	1.00
	8	0.94	0.97	1.01	1.01	1.01	1.02
	16	0.97	0.98	1.00	1.00	1.00	1.01
	32	1.05	1.03	1.03	1.03	1.02	1.00

Notes: each entry reports the ratio of the RMSFE obtained with different LPF cut-off choices, always with the nowcast, relative to the RMSFE obtained with the optimal cut-off in the sample 1984Q1-2013Q3 without the nowcast. As such, for each variable, the first line of the table is exactly the same as that in Table 2 panel (B). The optimal cut-off for each variable and forecast horizon is the cut-off minimizing the RMSFE in a given sample. The table presents the ratios obtained by determining the cut-off period in five alternative ways: the first corresponds to choosing the optimal cut-off(s) in 1984Q1-2013Q3, the evaluation sample (see Table 1 for further details); the second amounts to choosing the optimal cut-off(s) in a different sample, 1974Q1-1983Q4, i.e., using data available before the evaluation period (see Table 1); and then, for robustness, the cut-off is kept constant at 8, 16 or 32 quarters respectively.

4 Conclusions

Through a pseudo-real time exercise, we have shown that extending several representative time series with an SPF nowcast is a promising approach to enhance the forecast performance of various statistical methods. While SPF forecasts still prove hard to beat, appending those nowcasts to the observed series improves model performance in the short-term and actually becomes a preferred approach when forecasting at longer horizons ($h > 4$). Further, we have shown that, relative to an array of alternative methods, a simple univariate low-pass filter delivers consistently superior predictions, complementing the analysis of Valle e Azevedo and Pereira (2013). However, some instability in our results (across variables/horizons) calls for further research, namely through the application to a broader set of variables and/or by experimenting with other sources of nowcasts so as to get a better grap of the full forecast potential offered by this simple approach.

References

[1] Altissimo, F., Cristadoro, R., Forni, M., Lippi, M. and G. Veronese (2010). "New EuroCoin: Tracking Economic Growth in Real-time", Review of Economics and Statistics, 92(4):1024-1034.

[2] Ang, A., Bekaert, G. and M. Wei (2007). "Do Macro Variables, Asset Markets, or Surveys Forecast Inflation Better?", Journal of Monetary Economics, 54(4):1163-1212.

[3] Angelini, E., Camba-Mendez, G., Giannone, D., Reichlin, L. and Rünstler, G. (2011). "Short-term forecasts of euro area GDP growth", The Econometrics Journal, 14(1):25-44.

[4] Andreou, E., Ghysels, E. and A. Kourtellos (2011). "Forecasting with mixed-frequency data", in M. Clements and D. F. Hendry, eds, 'The Oxford Handbook on Economic Forecasting', Oxford University Press, chapter 8, pp.225-267.

[5] Baghestani, H. (2012). "Are Professional Forecasts of Growth in U.S. Business Investment Rational?", Economics Letters, 114(1):132-135.

[6] Baghestani, H. (2009). "Survey Evidence on Forecast Accuracy of U.S. Term Spreads", Review of Financial Economics, 18(3):156-162.

[7] Bernanke, B. S., Boivin, J. and P. Eliasz (2005). “Measuring Monetary Policy: A Factor Augmented Vector Autoregressive (FAVAR) Approach”, Quarterly Journal of Economics, 120(1):387-422.

[8] Christiano, L. and T. Fitzgerald (2003).“The band-pass filter”, International Economic Review, 44(2):435-465.

[9] Clements, M. and A. B. Galvão (2009). “Forecasting US output growth using leading indicators: an appraisal using MIDAS models”, Journal of Applied Econometrics, 24(7):1187-1206.

[10] Clements, M. and A. B. Galvão (2008). “Macroeconomic Forecasting With Mixed-Frequency Data”, Journal of Business and Economic Statistics, 26(4):546-554.

[11] Croushore, D. (2008). “An evaluation of inflation forecasts from surveys using real-time data”, Working Paper No. 06-19, Federal Reserve Bank of Philadelphia.

[12] Croushore, D. (1993). “Introducing: The Survey of Professional Forecasters”, Federal Reserve Bank of Philadelphia, Business Review (November/December 1993), pp. 3-13.

[13] Diebold, F.X. and R. S. Mariano (1995). “Comparing Predictive Accuracy”, Journal of Business and Economic Statistics 13(3):253-263.

[14] Faust, J. and J. H. Wright (2012). “Forecasting Inflation”, June 27, 2012 Draft for Handbook of Forecasting.

[15] Faust, J. and J. H. Wright (2009). “Comparing Greenbook and Reduced Form Forecasts Using a Large Real-time Dataset”, Journal of Business and Economic Statistics, 27(4):468-479.

[16] Fernandez, C., Ley, E. and M.F.J. Steel (2001). “Model Uncertainty in Cross-Country Growth Regressions”, Journal of Applied Econometrics, 16(5):563-576.

[17] Giannone, D., Reichlin, L. and D. Small (2008). “Nowcasting: The real-time informational content of macroeconomic data”, Journal of Monetary Economics, 55(4):665-676.

[18] Giannone, D., Lenza, M. and L. Reichlin (2008a). “Explaining The Great Moderation: It Is Not The Shocks”, Journal of the European Economic Association, 6(2-3):621-63.

[19] Kolasa, M., Rubaszek, M., and P. Skrzypczynski (2012). "Putting the New Keynesian DSGE Model to the Real-Time Forecasting Test", Journal of Money, Credit and Banking 44(7):1301-1324.

[20] Koop, G. and S. Potter (2003). "Forecasting in Large Macroeconomic Panels Using Bayesian Model Averaging", Federal Reserve Bank of New York Staff Report 163.

[21] Liebermann, J. (2013). "Real-Time Nowcasting of GDP: A Factor Model vs. Professional Forecasters", Oxford Bulletin of Economics and Statistics, forthcoming.

[22] Marcellino, M., Stock, J.H. and M. W. Watson (2006). "A Comparison of Direct and Iterated Multistep AR methods for Forecasting Macroeconomic Time Series", Journal of Econometrics, 135(1-2):499-526.

[23] McConnell, M. and G. Perez-Quiros (2000)."Output Fluctuations in the United States: What Has Changed Since the Early 1980's?", American Economic Review, 90(5):1464-1476.

[24] Rubaszek, M., and P. Skrzypczynski (2008). "On the Forecasting Performance of a Small-Scale DSGE Model", International Journal of Forecasting, 24(3):498-512.

[25] Stock, J.H. and M.W. Watson. (2002a). " Macroeconomic Forecasting Using Diffusion Indexes", Journal of Business and Economic Statistics, 20(2):147-162.

[26] Stock, J.H. and M.W. Watson (2002b). "Forecasting Using Principal Components from a Large Number of Predictors", Journal of the American Statistical Association, 97(460):1167-79.

[27] Stark, T. (2010). "Realistic evaluation of real-time forecasts in the Survey of Professional Forecasters", Federal Reserve Bank of Philadelphia, Research Rap Special Report, May 2010.

[28] Valle e Azevedo, J. and A. Pereira (2013). "Macroeconomic Forecasting Using Low-Frequencty Filters", Banco de Portugal WP 1-2013.

[29] Wildi, M. (1998). "Detection of compatible turning-points and signal-extraction for non-stationary time series", Operations Research Proceedings 1998, Springer, pp. 293–299.

[30] Wildi, M. (2008). Real-Time Signal Extraction, Beyond Maximum Lykelihood Principles, IDP-Working book.

[31] Wolters, M. H. (2013). "Evaluating Point and Density Forecasts of DSGE Models", Journal of Applied Econometrics, forthcoming.

[32] Wright, J. H. (2009). "Forecasting US Infation by Bayesian Model Averaging", Journal of Forecasting, 28(2):131-144.

Data Appendix

SPF forecasts are taken from the website of the Federal Reserve Bank of Philadelphia and cover the period 1968Q4-2013Q3.[5] We take as observations of the seven representative macroeconomic series (against which forecasts are compared) the October 2013 vintage of data. When necessary, all the series are converted to quarterly by averaging the observations within each quarter (this matches the target of SPF panelists). Except for unemployment and interest rates, which are in first differences, all these series are in log differences. Except for interest rates, all published data is seasonally adjusted, in accordance with the target of SPF's forecasts. Prior to 1992, real output forecasts refer to nominal GNP. GDP deflator forecasts refer to GNP deflator prior to 1992, to GDP deflator from 1992 til 1995 and to chain-weighted price index for GDP since 1996.

Our panel of predictors is very similar to the monthly panel in Stock and Watson (2002a) and covers the period from 1959 January/Q1 to 2013 September/Q3 2013. Some variables were replaced by similar variables due to lack of free public availability. The series were taken from the FRED database (Federal Reserve Bank of St. Louis). The $n = 79$ available time series were realigned to account for release delays.

The following tables describe these series along with Philadelphia SPF's and FRED's id codes as well as the sample period.

[5] http://www.phil.frb.org/econ/spf/spfpage.html. See also Croushore (1993) for background information.

Title	FRED id	Phil-SPF id	Transf.[1]	Sample period[2]	Description[3]
Real GNP/GDP	ROUTPUT	RGDP	Δln	1959:Q1-2013:Q3	SAAR; Billions of chained 2009 dollars
Price Index for GNP/GDP	P	PGDP	Δln	1959:Q1-2013:Q3	SA; Index 2009=100
Consumer Price Index	CPI	CPI	Δln	1959:M1-2013:M09	SA; Index 1982-84=100
Real Gross Private Domestic Investment - Residential	RINVRESID	RRESINV	Δln	1959:Q1-2013:Q3	SAAR; Billions of chained 2009 dollars
Housing Starts	HSTARTS	HOUSING	Δln	1959:M1-2013:M09	SAAR; Thousands of units
Unemployment Rate	RUC	UNEMP	Δlev	1959:M1-2013:M09	SA; Percent
3-Month Treasury Bill Rate	TB3MS	TBILL	Δlev	1959:M1-2013:M09	NA; Percent

(1) Δln - first difference of the logarithm of the series and Δlev - first difference of the level of the series.
(2) M stands for month and Q for quarter.
(3) SAAR - seasonally adjusted at annual rate, SA - seasonally adjusted and NA - not applicable.

The table below describes our panel of predictors. All series come from the FRED database of the Federal Reserve Board of St. Louis. Monthly predictors are converted to quarterly data (as 3 month averages) before any other transformations.

Title	FRED id	Transf.$^{(1)}$	Sample Period$^{(2)}$	Description$^{(3)}$
Real Gross Domestic Product	GDPC1	Δln	1959:Q1-2013:Q3	SAAR; Billions of chained 2009 dollars
Real Disposable Personal Income	DPIC96	Δln	1959:Q1-2013:Q3	SAAR; Billions of chained 2009 dollars
Real Personal Consumption Expenditures	PCECC96	Δln	1959:Q1-2013:Q3	SAAR; Billions of chained 2009 dollars
Real Personal Consumption Expenditures: Services	DSERRA3Q086SBEA	Δln	1959:Q1-2013:Q3	SA; chain-type quantity index, 2009=100
Real Personal Consumption Expenditures: Durable Goods	DDURRA3Q086SBEA	Δln	1959:Q1-2013:Q3	SA; chain-type quantity index, 2009=100
Real Personal Consumption Expenditures: Nondurable Goods	DNDGRA3Q086SBEA	Δln	1959:Q1-2013:Q3	SA; chain-type quantity index, 2009=100
Real Private Residential Fixed Investment	B011RA3Q086SBEA	Δln	1959:Q1-2013:Q3	SA; chain-type quantity index, 2009=100
Real Private Nonresidential Fixed Investment	B008RA3Q086SBEA	Δln	1959:Q1-2013:Q3	SA; chain-type quantity index, 2009=100
Real State & Local Consumption Expenditures & Gross Investment	B829RA3Q086SBEA	Δln	1959:Q1-2013:Q3	SA; chain-type quantity index, 2009=100
Real Federal Consumption Expenditures & Gross Investment	B823RA3Q086SBEA	Δln	1959:Q1-2013:Q3	SA; chain-type quantity index, 2009=100
Consumer Price Index for All Urban Consumers: All Items	CPIAUCSL	Δln	1959:M1-2013:M09	SA; Index 1982-84=100
Consumer Price Index for All Urban Consumers: All Items Less Food	CPIULFSL	Δln	1959:M1-2013:M09	SA; Index 1982-84=100
Consumer Price Index for All Urban Consumers: All Items Less Food & Energy	CPILFESL	Δln	1959:M1-2013:M09	SA; Index 1982-84=100
Consumer Price Index for All Urban Consumers: Apparel	CPIAPPSL	Δln	1959:M1-2013:M09	SA; Index 1982-84=100
Consumer Price Index for All Urban Consumers: Medical Care	CPIMEDSL	Δln	1959:M1-2013:M09	SA; Index 1982-84=100
Consumer Price Index for All Urban Consumers: Transportation	CPITRNSL	Δln	1959:M1-2013:M09	SA; Index 1982-84=100
Gross Domestic Product: Chain-type Price Index	GDPCTPI	Δln	1959:Q1-2013:Q3	SA; Index 2005=100
Personal Consumption Expenditures: Chain-type Price Index	PCEPI	Δln	1959:M1-2013:M09	SA; Index 2005=100
Producer Price Index: All Commodities	PPIACO	Δln	1959:M1-2013:M09	NSA; Index 1982=100
Producer Price Index: Crude Materials for Further Processing	PPICRM	Δln	1959:M1-2013:M09	SA; Index 1982=100
Producer Price Index: Finished Consumer Goods	PPIFCG	Δln	1959:M1-2013:M09	SA; Index 1982=100
Producer Price Index: Finished Goods	PPIFGS	Δln	1959:M1-2013:M09	SA; Index 1982=100
Producer Price Index: Intermediate Materials: Supplies & Components	PPIITM	Δln	1959:M1-2013:M09	SA; Index 1982=100
Industrial Production Index	INDPRO	Δln	1959:M1-2013:M09	SA; Index 2007=100
Industrial Production: Consumer Goods	IPCONGD	Δln	1959:M1-2013:M09	SA; Index 2007=100
Industrial Production: Durable Consumer Goods	IPDCONGD	Δln	1959:M1-2013:M09	SA; Index 2007=100
Industrial Production: Nondurable Consumer Goods	IPNCONGD	Δln	1959:M1-2013:M09	SA; Index 2007=100
Industrial Production: Durable Materials	IPDMAT	Δln	1959:M1-2013:M09	SA; Index 2007=100

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continued

Title	FRED id	Transf.(1)	Sample Period(2)	Description(3)
Industrial Production: Nondurable Materials	IPNMAT	Δln	1959:M1-2013:M09	SA; Index 2007=100
Industrial Production: Business Equipment	IPBUSEQ	Δln	1959:M1-2013:M09	SA; Index 2007=100
Industrial Production: Final Products (Market Group)	IPFINAL	Δln	1959:M1-2013:M09	SA; Index 2007=100
Industrial Production: Materials	IPMAT	Δln	1959:M1-2013:M09	SA; Index 2007=100
ISM Manufacturing: PMI Composite Index	NAPM	lev	1959:M1-2013:M09	SA; Index
ISM Manufacturing: Employment Index	NAPMEI	lev	1959:M1-2013:M09	SA; Index
ISM Manufacturing: Inventories Index	NAPMII	lev	1959:M1-2013:M09	SA; Index
ISM Manufacturing: New Orders Index	NAPMNOI	lev	1959:M1-2013:M09	SA; Index
ISM Manufacturing: Production Index	NAPMPI	lev	1959:M1-2013:M09	SA; Index
ISM Manufacturing: Supplier Deliveries Index	NAPMSDI	lev	1959:M1-2013:M09	SA; Index
Housing Starts: Total: New Privately Owned Housing Units Started	HOUST	ln	1959:M1-2013:M09	SAAR; Thousands of units
Housing Starts in Midwest Census Region	HOUSTMW	ln	1959:M1-2013:M09	SAAR; Thousands of units
Housing Starts in Northeast Census Region	HOUSTNE	ln	1959:M1-2013:M09	SAAR; Thousands of units
Housing Starts in South Census Region	HOUSTS	ln	1959:M1-2013:M09	SAAR; Thousands of units
Housing Starts in West Census Region	HOUSTW	ln	1959:M1-2013:M09	SAAR; Thousands of units
Real Exports of Goods & Services	EXPGSC96	Δln	1959:Q1-2013:Q3	SAAR; Billions of chained 2009 dollars
Civilian Unemployment Rate	UNRATE	lev	1959:M1-2013:M09	SA; Percent
Civilians Unemployed - Less Than 5 Weeks	UEMPLT5	Δln	1959:M1-2013:M09	SA; Thousands of persons
Civilians Unemployed for 5-14 Weeks	UEMP5TO14	Δln	1959:M1-2013:M09	SA; Thousands of persons
Civilians Unemployed for 15-26 Weeks	UEMP15T26	Δln	1959:M1-2013:M09	SA; Thousands of persons
Civilians Unemployed for 27 Weeks and Over	UEMP27OV	Δln	1959:M1-2013:M09	SA; Thousands of persons
Civilians Unemployed - 15 Weeks & Over	UEMP15OV	Δln	1959:M1-2013:M09	SA; Thousands of persons
Average (Mean) Duration of Unemployment	UEMPMEAN	Δln	1959:M1-2013:M09	SA; Weeks
Civilian Employment	CE16OV	Δln	1959:M1-2013:M09	SA; Thousands of persons
All Employees: Manufacturing	MANEMP	Δln	1959:M1-2013:M09	SA; Thousands
All Employees: Nondurable goods	NDMANEMP	Δln	1959:M1-2013:M09	SA; Thousands
All Employees: Service-Providing Industries	SRVPRD	Δln	1959:M1-2013:M09	SA; Thousands
All Employees: Construction	USCONS	Δln	1959:M1-2013:M09	SA; Thousands
All Employees: Financial Activities	USFIRE	Δln	1959:M1-2013:M09	SA; Thousands

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continued

Title	FRED id	Transf.(1)	Sample Period(2)	Description(3)
All Employees: Goods-Producing Industries	USGOOD	Δln	1959:M1-2013:M09	SA; Thousands
All Employees: Government	USGOVT	Δln	1959:M1-2013:M09	SA; Thousands
All Employees: Mining and logging	USMINE	Δln	1959:M1-2013:M09	SA; Thousands
All Employees: Total Private Industries	USPRIV	Δln	1959:M1-2013:M09	SA; Thousands
All Employees: Trade, Transportation & Utilities	USTPU	Δln	1959:M1-2013:M09	SA; Thousands
All Employees: Retail Trade	USTRADE	Δln	1959:M1-2013:M09	SA; Thousands
All Employees: Durable goods	DMANEMP	Δln	1959:M1-2013:M09	SA; Thousands
Compensation of Employees: Wages & Salary Accruals	WASCUR	Δln	1959:Q1-2013:Q3	SAAR; Billions of dollars
Average Weekly Hours of Production and Nonsupervisory Employees: Manufacturing	AWHMAN	Δln	1959:M1-2013:M09	SA; Hours
Average Weekly Overtime Hours of Production and Nonsupervisory Employees: Manufacturing	AWOTMAN	Δln	1959:M1-2013:M09	SA; Hours
3-Month Treasury Bill: Secondary Market Rate	TB3MS	Δlev	1959:M1-2013:M09	NA; Percent
6-Month Treasury Bill: Secondary Market Rate	TB6MS	Δlev	1959:M1-2013:M09	NA; Percent
1-Year Treasury Constant Maturity Rate	GS1	Δlev	1959:M1-2013:M09	NA; Percent
10-Year Treasury Constant Maturity Rate	GS10	Δlev	1959:M1-2013:M09	NA; Percent
5-Year Treasury Constant Maturity Rate	GS5	Δlev	1959:M4-2013:M09	NA; Percent
Effective Federal Funds Rate	FEDFUNDS	Δlev	1959:M1-2013:M09	NA; Percent
Moody's Seasoned Aaa Corporate Bond Yield	AAA	Δlev	1959:M1-2013:M09	NA; Percent
Moody's Seasoned Baa Corporate Bond Yield	BAA	Δlev	1959:M1-2013:M09	NA; Percent
Corporate Profits After Tax	CP	Δln	1959:Q1-2013:Q3	SAAR; Billions of dollars
M1 Money Stock	M1SL	Δln	1959:M1-2013:M09	SA; Billions of dollars
M2 Money Stock	M2SL	Δln	1959:M1-2013:M09	SA; Billions of dollars
Total Nonrevolving Credit Outstanding	NONREVSL	Δln	1959:M1-2013:M09	SA; Billions of dollars

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