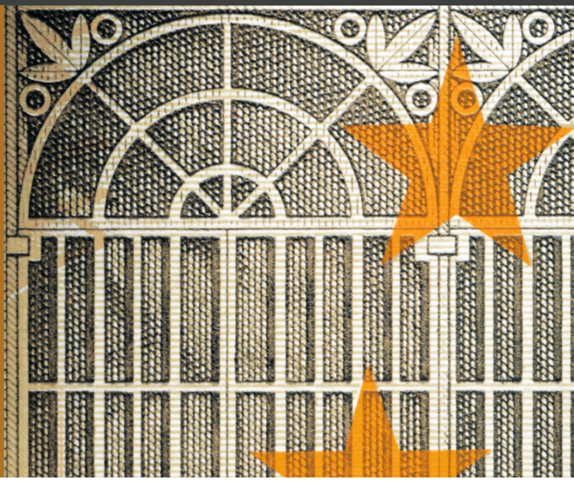

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February 2013

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Macroeconomic Forecasting using Low-Frequency Filters*

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Abstract

We explore the use of univariate low-frequency filters in macroeconomic forecasting. This amounts to targeting only specific fluctuations of the time series of interest. We show through simulations that such approach is warranted and, using US data, we confirm empirically that consistent gains in forecast accuracy can be obtained in comparison with a variety of other methods. There is an inherent arbitrariness in the choice of the cut-off defining low and high frequencies, but we show that some patterns characterize the implied optimal (for forecasting) degree of smoothing of the key macroeconomic indicators we analyze. For most variables the optimal choice amounts to disregarding fluctuations well below the standard business cycle cut-off of 32 quarters while generally increasing with the forecast horizon; for inflation and variables related to housing this cut-off lies around 32 quarters for all horizons, which is below the optimal level for federal spending.

JEL Classification: C14, C32, C51, C53

Keywords: Macroeconomic Forecasting, Low-frequency Filtering

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1 Introduction

This paper considers univariate low-frequency filters applied to macroeconomic forecasting. The idea is to project, or target, only low frequencies of the time series of interest onto past observations, or using a low-pass filter applicable in real-time. This may be more efficient than targeting the original series, which contains (mostly) unpredictable high-frequency components, specially at long horizons. This approach follows the principle of decoupling model/parameter estimation from forecasting or, more generally, signal extraction. This means that forecasts are not computed as the model implied "optimal" forecasts (under correct specification and true parameter values) but, instead, they are the solution to a general signal extraction problem that imposes little or no parametric structure to the moments of the data (see Wildi 2008 for an exhaustive analysis of this distinction). Here we additionally reduce the problem of forecasting into one of predicting a smooth (or filtered) version of the time series of interest, see Altissimo et al. (2010) for a similar approach.

We perform a simple Monte Carlo simulation to show that even when the parameters of a very parsimonious autoregression (AR) are efficiently estimated, the forecasts produced by the typical AR forecast function are often outperformed by a low-frequency projection (filter) using the same information. Further, we show that using this method produces interesting and consistent forecast accuracy gains in practice, even when compared to methods that explore information from a large panel of predictors. We conduct a pseudo out-of-sample forecasting exercise focusing on 13 key US macroeconomic indicators (all of them forecasted in the Philadelphia Survey of Professional Forecasters, SPF).

A crucial choice when using this method is the cut-off defining low and high frequencies. The optimal cut-off may vary across series and forecast horizons but we show that clear patterns characterize groups of time series in terms of the implied optimal degree of smoothing. Further, the results are robust to relevant deviations from this optimal degree of smoothing. For most variables the optimal choice amounts to disregarding fluctuations well below the standard business cycle cut-off of 32 quarters while generally increasing (slowly) with the forecast horizon; for the two inflation measures and variables related to housing this cut-off lies around 32 quarters for all horizons. This is below the optimal level for federal spending, which lies around 44-48 quarters.

The outline of the paper is as follows: in section 2 we make clear how the low-frequency projections are constructed. Section 3 presents some Monte Carlo results. Section 4 presents a pseudo out-of-sample forecasting exercise, comparing low-frequency projections with a host of alternatives. Section 5 concludes.

2 Real-Time Low-frequency Filtering

Suppose we are interested in forecasting y_t, assumed weakly stationary, h periods ahead. Our approach amounts simply to predicting a smooth version of y_{t+h}, or $y_{t+h}^{Low} = B(L)y_{t+h}$, where $B(L) = \sum_{j=-\infty}^{\infty} B_j L^j$ is just a low-pass filter eliminating fluctuations with period below a specified cut-off period. The weights of $B(L)$ are well-known and given by:

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

We then regard predictions of y_{t+h}^{Low} as forecasts of y_{t+h} itself. Clearly, if the power of the series is concentrated at low frequencies, an accurate prediction of y_{t+h}^{Low} will also be an accurate forecast of y_{t+h}. Now, on the one hand, if more (high) frequencies are excluded (i.e., the cut-off period or smoothness of the target increase) we will be giving up on more of the variance of y_{t+h}. On the other hand, focusing on predictions of y_{t+h}^{Low} may lead to a superior forecast performance if the high frequencies of y_t convey little information about y_{t+h}. We need however to decide on the cut-off period defining low and high frequencies whereas the optimal (for forecasting) implied degree of smoothness may vary with the forecast horizon and with the characteristics of y_t. We will deal explicitly with this issue within a simulation exercise and in the analysis of the forecast performance of the low-frequency projections, showing that there are interesting patterns characterizing the optimal degree of smoothing across the macroeconomic indicators under analysis.

In practice we want to predict y_{T+h}^{Low} given the finite sample $Y_T = \{y_t\}_{t=1}^{T}$. y_{T+h}^{Low} can be predicted by $\widehat{y}_{T+h}^{Low}$, a weighted sum of observations of Y_T:

$$\widehat{y}_{T+h}^{Low} = \alpha_0 + \sum_{j=0}^{p} \widehat{B}_j^p y_{T-j} \tag{1}$$

To obtain $\widehat{y}_{T+h}^{Low}$ we choose the weights $\{\widehat{B}_j^p\}_{j=0,\ldots,p}$ and α_0 that solve the following problem:

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

where the information set is implicitly restricted by p, the number of past observations considered. We use the solution to problem (2) discussed in Wildi (1998) and Christiano and Fitzgerald (2003) for stationary $\{y_t\}$.[1] The weights of the filter are obtained by simply solving a linear system. The solution depends only on the second moments (or spectrum) of y_t, which we estimate non-parametrically, and on the weights of the "ideal" filter $B(L)$. Define $\widehat{B} = (\alpha_0, \widehat{B}_p^p, \widehat{B}_{p-1}^p, ..., \widehat{B}_0^p)'$. The linear system solved to recover the solution $\widehat{B}$ is the following:

$$V = Q\widehat{B} \tag{3}$$

where Q is a $(p+2)\times(p+2)$ matrix that depends only on the second moments of y_t and V is a vector of dimension $p+2$ that depends also on the second moments of y_t but also on the weights of the infinite sample filter $(B(L))$. The exact expressions for V and Q are a straightforward specialization of the ones in Christiano and Fitzgerald (2003) or in Valle e Azevedo (2011) for $\{y_t\}$ following a finite moving-average process.

In this paper we will always set $p = 50 - h$ (larger values of p and no dependence on h lead to negligible differences in the predictions). We estimate the needed autocovariance function (or spectrum) of y_t based on a standard non-parametric estimator of the spectrum, given by:

$$\widehat{S}_y(\omega) = \frac{1}{2\pi}(\widehat{\gamma}(0) + \sum_{k=1}^{M(T)} \kappa(k)\widehat{\gamma}(k)(e^{i\omega k} + e^{-i\omega k})$$

[1] We should note that it would be feasible to use an OLS-type projection to forecast y_{T+h}^{Low} and hence y_{T+h}. First, one would obtain an in-sample accurate measure of y_t^{Low}, obtained with the Baxter and King (1999) filter ($\widehat{y}_t^{Low} = \sum_{j=-m}^{m} B_j y_{t-j}$) and then regress $\widehat{y}_t^{Low}$ on past observations of y_t. More specifically, one could always approximate y_t^{Low} up to $T-m$, project this onto y_t dated $T-m-h$ and earlier (h is the forecast horizon) and then use at time T the estimated projection coefficients to forecast y_{T+h}^{Low}. If m is small, few observations of the dependent variable are lost in the beginning and end of the sample. However, in our analysis a large m is needed because potentially very low frequencies are to be kept, which requires more observation of y_t being averaged out. In any case we have tried this simpler approach but results were poor. Our conjecture is that an OLS type projection resembling a direct solution to problem (2) requires a potentially large number of lags of y_t (for instance, we will use $p = 50 - h$ lags in the filter) which leads to overfitting and poor out-of-sample behavior.

where $\kappa(k,T) = (1 - \dfrac{k}{M(T)+1})$ denotes the Bartlett lag window, $\widehat{\gamma}(k)$, $k = 0,1,...,M(T)$ is the sample autocovariance of y_t at lag k and the truncation point $M(T) < T$ is a function of the sample size T. $M(T)$ is typically required to grow slower than T to guarantee consistency of $\widehat{S}_y(\omega)$. For all empirical purposes we set in this estimator $M = 30$ (in the range $20 < M < 40$ results are very similar).

3 Monte Carlo Results

We consider time series $\{y_t\}$ generated by the simple AR process of order 1, $y_t = \theta + \rho y_{t-1} + \varepsilon_t$, where $\varepsilon_t \sim N(0, \sigma_\epsilon^2)$ is an i.i.d. sequence and $y_0 = 0$. We set $\theta = 0$ but will not assume the mean of the process is known. σ_ϵ^2 is set to one and $\rho \in \{0.5, 0.8, 0.95\}$.[2] This exercise is certainly far from complete within the finite sample world but it provides, we believe, relevant insights.

We generate 5000 sequences $\{y_t\}_{t=1}^{T+h}$ for $1 \leq h \leq 12$ and $T = 100$ or 200. We look at forecasts generated by the AR forecast function, $\hat{y}_{T+h|T} = \widehat{\theta}\sum_{j=1}^{h}\widehat{\rho}^{j-1} + \widehat{\rho}^h y_T$, where $\widehat{\theta}$ and $\widehat{\rho}$ are obtained by OLS within the sample $\{y_t\}_{t=1}^{T}$. These are compared with low-pass filter forecasts based on the same information, $\widehat{y}_{T+h|T}^{Low}$, say, for cut-off periods ranging from 2 (or no-smoothing) through to 84 periods. For the sake of consistency the settings of the filter are exactly those employed in the empirical exercise: $p = 50 - h$ and $M = 30$. We thus avoid trying to optimize over p or M the Monte Carlo performance of the filter. We then compute, across simulations, forecast errors and the root mean squared forecast error (RMSFE) for the two methods. Table 1 presents the RMSFE of the low-pass filter forecasts relative to that obtained with the simple AR model. Values below 1 indicate that, in a mean squared error sense, low-pass filter forecasts outperform AR forecasts.

An immediate conclusion is that low-pass filter forecasts generally require, for better results, more smoothing (larger cut-off period) the larger is the forecast horizon. Still, various cut-off periods lead to similar results when $\rho = 0.5$ and $h > 1$ or when $\rho = 0.8$ and $h > 2$. Quite interestingly, when h is large and $T = 100$, low-pass filter forecasts often outperform the AR forecast when $\rho = 0.8$ and specially when $\rho = 0.95$. As expected, this advantage decreases with a larger ($T = 200$) sample

[2] This is only for reasons of parsimony. We have considered a much finer grid for ρ. The results for $\rho < 0.5$ are quantitatively and qualitatively similar to those obtained with $\rho = 0.5$. Further, the performance of the low-pass filter changes quite "continuously" from $\rho = 0.5$ through to $\rho = 0.8$ and from $\rho = 0.8$ through to $\rho = 0.95$ and above, according to the patterns described below with only $\rho \in \{0.5, 0.8, 0.95\}$.

Table 1

Simulation Results. Relative (to AR model) RMSFE of low-pass filter forecasts by cut-off period and forecast horizon.

$\rho = 0.5$	**T=100**			Forecast Horizon				**T=200**			Forecast Horizon			
	1	2	4	6	8	10	12	1	2	4	6	8	10	12
Cut-off														
2	1.06	1.06	1.02	1.00	0.99	1.03	0.99	1.04	1.04	1.04	1.03	1.00	1.00	1.00
4	1.06	1.07	1.03	1.01	1.00	1.02	0.98	1.05	1.05	1.03	1.03	1.01	1.00	1.01
6	1.04	1.05	1.03	1.01	1.00	1.03	0.98	1.02	1.04	1.05	1.04	1.00	1.00	1.00
8	1.06	1.01	1.01	1.02	0.99	1.01	0.99	1.05	1.02	1.03	1.02	1.03	1.01	1.00
12	1.12	1.04	1.01	1.00	1.01	1.03	0.99	1.10	1.03	1.03	1.04	1.02	0.99	0.99
18	1.16	1.04	1.04	1.03	0.99	1.00	0.99	1.15	1.08	1.04	1.02	1.00	1.01	1.01
24	1.15	1.04	1.02	1.04	1.01	1.00	0.99	1.20	1.09	1.02	1.02	1.01	1.02	1.02
32	1.19	1.05	1.03	1.05	1.02	1.02	0.98	1.23	1.10	1.03	1.02	1.00	1.01	1.01
48	1.23	1.04	1.01	1.03	1.01	1.01	0.98	1.27	1.09	1.04	1.00	1.00	0.99	0.98
60	1.24	1.04	1.02	1.02	1.01	1.00	0.97	1.28	1.08	1.03	1.01	1.01	0.99	0.98
72	1.24	1.03	1.03	1.02	1.01	1.00	0.97	1.29	1.08	1.03	1.01	1.01	1.00	0.98
84	1.24	1.03	1.02	1.01	1.00	1.00	0.97	1.29	1.07	1.02	1.01	1.01	1.00	0.99

$\rho = 0.8$	**T=100**			Forecast Horizon				**T=200**			Forecast Horizon			
	1	2	4	6	8	10	12	1	2	4	6	8	10	12
Cut-off														
2	1.09	1.08	1.03	1.03	1.00	0.99	0.96	1.04	1.05	1.02	1.03	1.02	1.00	0.98
4	1.07	1.07	1.03	1.02	1.01	0.99	0.96	1.02	1.04	1.03	1.03	1.02	1.00	0.98
6	1.05	1.03	1.05	1.02	1.00	0.99	0.95	1.06	1.04	1.03	1.02	1.02	1.00	0.98
8	1.11	1.01	1.02	1.03	1.00	0.98	0.95	1.09	1.02	1.02	1.03	1.02	0.99	0.98
12	1.24	1.01	1.00	1.02	1.02	0.98	0.97	1.21	1.03	1.01	1.03	1.04	1.00	0.98
18	1.48	1.09	0.98	0.99	1.00	0.99	0.97	1.38	1.06	0.99	1.01	1.00	1.00	1.00
24	1.67	1.21	1.00	0.98	0.95	0.98	0.98	1.59	1.14	1.00	0.99	0.98	0.98	0.99
32	1.81	1.28	1.04	1.00	0.97	0.97	0.96	1.82	1.23	1.01	1.01	1.01	0.99	0.98
48	2.06	1.38	1.07	1.01	1.01	0.98	0.96	2.16	1.34	1.04	1.00	0.99	0.99	0.97
60	2.20	1.43	1.09	1.01	1.01	0.98	0.96	2.34	1.41	1.07	0.99	0.99	0.99	0.97
72	2.28	1.46	1.10	1.02	1.02	0.98	0.96	2.48	1.47	1.09	1.00	1.00	0.99	0.98
84	2.34	1.47	1.11	1.02	1.01	0.98	0.96	2.58	1.51	1.11	1.00	1.00	0.99	0.98

$\rho = 0.95$	**T=100**			Forecast Horizon				**T=200**			Forecast Horizon			
	1	2	4	6	8	10	12	1	2	4	6	8	10	12
Cut-off														
2	1.33	1.25	1.14	1.09	1.03	1.03	0.93	1.08	1.11	1.17	1.17	1.17	1.14	1.09
4	1.18	1.24	1.14	1.09	1.03	1.03	0.93	1.05	1.11	1.16	1.17	1.16	1.14	1.09
6	1.19	1.17	1.16	1.09	1.02	1.04	0.92	1.05	1.08	1.18	1.16	1.16	1.14	1.09
8	1.21	1.13	1.15	1.11	1.03	1.02	0.94	1.06	1.06	1.17	1.19	1.16	1.12	1.09
12	1.39	1.15	1.08	1.08	1.06	1.05	0.92	1.16	1.09	1.12	1.17	1.19	1.16	1.10
18	1.70	1.28	1.06	1.04	1.01	1.03	0.94	1.45	1.16	1.10	1.12	1.15	1.14	1.11
24	1.93	1.39	1.08	1.03	0.99	1.01	0.93	1.66	1.24	1.12	1.09	1.11	1.11	1.09
32	2.24	1.53	1.08	0.99	0.95	0.97	0.90	2.10	1.43	1.16	1.10	1.09	1.08	1.06
48	2.92	1.85	1.17	0.98	0.91	0.91	0.84	2.84	1.75	1.30	1.14	1.08	1.05	1.02
60	3.49	2.14	1.27	1.00	0.90	0.90	0.82	3.33	1.96	1.37	1.17	1.08	1.04	0.99
72	4.01	2.40	1.36	1.05	0.92	0.91	0.81	3.82	2.18	1.46	1.21	1.10	1.05	0.99
84	4.43	2.61	1.44	1.10	0.94	0.92	0.82	4.26	2.37	1.55	1.26	1.14	1.07	0.99

Note: Ratios below 1 are highlighted in grey size, although the distance between low-pass filter and AR forecasts is still negligible for $\rho = 0.5$ and $\rho = 0.8$ when $h > 4$. On the contrary, the performance of the low-pass filter deteriorates significantly over the AR when $\rho = 0.95$ and $h < 12$.

Overall, the results suggest that the low-pass filter can be useful, given small samples, to forecast persistent AR(1) series at long horizons. Further, for mild to low persistence the advantages or costs of using the filter are small. Finally, we should point out that it would be easy to present a Monte Carlo exercise more favorable to the univariate filter, e.g., by considering a less parsimonious AR process, choice of lag length by the AIC or BIC criteria or some sort of misspecification (e.g., a "small" moving average component). The results presented follow from a favorable scenario to the AR forecasts.[3]

4 Empirical Forecast results

4.1 Data and Pseudo out-of-sample design

We analyze 13 US macroeconomic indicators, whose forecasts are comparable with the quarterly forecasts disclosed by the Philadelphia Survey of Professional Forecasters (SPF). Specifically, we forecast the following series: Nominal GNP/GDP, Real GNP/GDP, Real Personal Consumption Expenditures, Price Index for GNP/GDP, Consumer Price Index, Real Gross Private Domestic Investment - Residential, Real Gross Private Domestic Investment - Nonresidential, Real Government Consumption and Gross Investment - State and Local, Real Government Consumption and Gross Investment - Federal, Housing Starts, Industrial Production Index, Unemployment Rate and 3-Month Treasury Bill Rate. We use the June 2011 vintage of these series available from the real-time data set of the Federal Reserve Bank of Philadelphia. The data spans 1959 January/Q1 through to 2010 December/Q4. To be consistent with SPF forecasts all monthly indicators are first aggregated quarterly as 3 month averages. Also, we apply log differences to all the series except for the unemployment rate and the 3-month treasury bill rate, to which we apply first differences in the levels. All relevant information about the indicators can be found in the data appendix. Besides the variables to be

[3]On the other hand, we are surely aware that the literature has produced finite sample corrections or combination methods that lead to forecasts more accurate than the estimated AR forecast function, see, e.g., Clements and Hendry (1998) and Kim (2003.)

forecasted, our dataset includes a panel of monthly predictors (aggregated quarterly as 3 month averages) which will be used in some multivariate methods, including methods that reduce information through factor analysis. A complete description of the panel can also be found in the data appendix.

Notice that we use for estimation and computation of forecast errors the June 2011 vintage of data, which can be subject to revisions and differs in general from the first publication. But except for this issue, our pseudo out-of-sample design simulates a real-time situation to produce forecasts with all models and methods while guaranteeing no advantage in terms of timing over SPF forecasts. More precisely, in order to forecast y_{t+h} at quarter t the information set available for each method for estimation and construction of forecasts contains data referring only to quarter t and earlier, including data that only becomes available around the middle of quarter $t+1$ (e.g., national accounts data) but before SPF panelists submit what we denote as h quarters ahead forecasts of y_t (i.e., forecasts of y_{t+h}).[4] To be clear, SPF participants report forecasts for what we denote as quarter $t+h$, $h = 1, 2, 3, 4$ in the middle of quarter $t+1$. This means that, especially in the case of forecasts of CPI inflation or 3 month T-bill rates, there is an informational advantage of the survey participants relative to the other methods in our pseudo-out-of-sample exercise.[5] In any case, this informational advantage is only a concern for very short horizons.

Finally, for methods other than the SPF we report results for horizons (in quarters) $h = 1, 2, 4, 6, 8$ and 12. The estimation sample starts always at 1959Q1 whereas the evaluation sample starts at 1984Q1, coinciding with the start of the Great Moderation (see e.g., Giannone, Lenza and Reichlin 2008 and McConnel and Perez-Quiros 2000) and ends at 2010Q4.[6]

[4]This also means that publication lags are taken into account. Thereafter, and depending on the forecasting model, we transform the data, extract factors, estimate coefficients and/or compute filter weights with only the observations in this information set.

[5]E.g., to forecast quarterly CPI inflation for 2012Q2 in the middle of 2012Q1, SPF panelists know the CPI figures until January 2012 and other information (such as oil prices) until mid-February. Now, we denote this forecast as a two quarter ahead forecast (i.e., $h = 2$) but compare it to forecasts (obtained with the other methods) constructed with information referring only to the end of December of 2011 and before while sometimes only available by mid-February. In the case of series released with national accounts, and because of release delays, the latest figures of these series known by SPF panelists coincide approximately with those contained in the information sets we build for each method (with the additional difference that we use in all methods the June 2011 vintage of data). E.g., the initial release of real output growth in mid-February of 2012 refers to the fourth quarter of 2011 and it is contained in the information sets we build for the forecast moment "2011:Q4". Still, SPF panelists surely make use of other information released until the middle of the quarter whereas we use only information referring to the previous quarter and before.

[6]We will later remark that we have repeated the analysis under various settings, including estimation with only post 1984 data and/or forecast evaluation over various sub-samples. These exercises do not change the main message of the paper and are available upon request. We omit them for reasons of parsimony.

4.2 Forecasting models and methods

Here we describe the forecasting models and methods against which we compare the simple univariate low-pass filter based forecasts. These range from simple univariate models to more sophisticated multivariate designs, including pooling-based forecasts. The competing methods follow:

- *Low-pass filter (LPF)*

  We use as forecast of y_{t+h} the estimated solution to problem (2), $\widehat{y}^{Low}_{t+h|t} = \alpha_0 + \sum_{j=0}^{p} \widehat{B}^p_j y_{t-j}$. We set $p = 50 - h$ and estimate second moments non-parametrically as described in section 2. As for the degree of smoothness, i.e., the cut-off period below which fluctuations will not be fitted, it will vary with the forecast horizon and the variable being forecasted. We address this issue in the next subsection.

- *Iterated autoregression (IAR)*

  We estimate $y_t = \rho_0 + \sum_{j=1}^{p} \rho_j y_{t-j} + \varepsilon_t$ by OLS to obtain in-sample estimates of the parameters. Then, the h-quarters ahead iterated 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 $i \leq t$. The lag order p is set equal to 4 in all cases, as suggested by results in Marcellino, Stock and Watson (2006) for quarterly data.[7]

- *Direct autoregression (DAR)*

  The h-quarters ahead forecasts are directly constructed from the equation $y_{t+h} = \rho_{0,h} + \sum_{j=1}^{p} \rho_{j,h} y_{t+1-j} + \varepsilon_{t+h}$. The parameters are estimated by OLS and the lag order p equals 4. More specifically, the direct forecast of y_{t+h} is:

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

[7] Here and in the methods that follow, we have verified that using the AIC or BIC criteria to choose the lag order does not change significantly the results. The same is true of specifications that impose a unit-root in the representation of y_t, whenever this hypothesis is reasonable (e.g., for inflation data).

- *Factor augmented autoregression (FAAR)*

  The autoregression model is augmented with the first m principal components, $\{z_{it}\}_{i=1}^{m}$, of a set of n additional 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:

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

  We set the lag order p equal to 4 and the number of factors m to 3.[8] 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. Again, a complete description of the predictors used in the forecasting exercise is provided in the data appendix.

- *Factor augmented vector autoregression (FAVAR)*

  Following Bernanke, Boivin and Eliasz (2005), we estimate the following factor augmented vector autoregression model $\zeta_t = \phi_0 + \sum_{j=1}^{s} \phi_j \zeta_{t-j} + \varepsilon_t$, 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 exactly the ones used to compute the FAAR forecasts.

- *Equal-weighted averaging (EWA)*

  Another way of embodying large information sets in the forecasting process amounts to pooling forecasts. Here we present combination forecasts that result from a simple average of n individual forecasts of y_{t+h}. Specifically, each individual forecast is computed from a direct forecasting regression model of the form $y_{t+h}^i = \rho_{0,h}^i + \sum_{j=1}^{p} \rho_{j,h}^i y_{t+1-j} + \beta_{i,h} x_{it} + \varepsilon_{t+h}^i$ for $i = 1, \ldots, n$ where p equals 4 and x_{it} stands for each one of the predictors included in the panel used to extract principal components. The regression coefficients are again estimated by OLS. Finally, the forecast of y_{t+h} submitted to evaluation is $\hat{y}_{t+h} = n^{-1} \sum_{i=1}^{n} \hat{y}_{t+h}^i$.[9]

[8] Here and in the method that follows, we have tried $m = 1, 2$ and 4. None of these values would imply a significantly different qualitative analysis.

[9] The consistent empirical results on increased forecast accuracy documented in a large literature support the use of such method for forecasting purposes (see, e.g., Diebold and Lopez 1996 or Hendry and Clements 2004). The method is first proposed in Bates and Granger (1969).

- *Bayesian model averaging (BMA)*

  BMA forecasts consist in a combination of individual forecasts where the aggregation scheme is grounded on Bayesian statistics. Generally, given a set of n models, M_i with $i = 1, \dots, n$, one defines a prior to the probability that the ith model is the true model, $P(M_i)$. With observed data, D, it is possible to compute the posterior probability that the ith model is the true model, $P(M_i/D)$. Then, these latter probabilities are used as weights while averaging the n individual forecasts from the specified models. A more detailed description and some applications of this method are given in Koop and Potter (2003), Wright (2009) and Faust and Wright (2009).

  For our forecasting exercise we follow to a great extent the assumptions made by Faust and Wright (2009). We begin by considering the n linear regression models used to compute the EWA forecasts. We assume a constant prior probability equal to $P(M_i) = n^{-1}$ for $i = 1, \dots, n$. As Fernandez, Ley and Steel (2001) we assume that $\varepsilon^i_{t+h} \sim N(0, \sigma^2)$ and that the marginal prior of σ is proportional to $\frac{1}{\sigma}$. We further assume that the prior of $\lambda_{i,h} = [\rho^i_{0,h} \quad \rho^i_{1,h} \dots \rho^i_{p,h} \quad \beta_{i,h}]'$ conditional on σ is $N(\overline{\lambda}_{i,h}, \phi(\sigma^2 \sum_{t=1}^{T}(w_{it}w_{it}^{'})^{-1}))$ where $w_{it} = [1 \quad y_t \quad y_{t-1} \dots y_{t+1-p} \quad x_{it}]'$ and $\overline{\lambda}_{i,h} = [\overline{\rho}^i_{0,h} \quad \overline{\rho}^i_{1,h} \dots \overline{\rho}^i_{p,h} \quad \overline{\beta}_{i,h}]'$, where $\overline{\beta}_{i,h} = 0$ and $\overline{\rho}^i_{0,h}, \overline{\rho}^i_{1,h}, \dots, \overline{\rho}^i_{p,h}$ are OLS estimates obtained in the sample 1959Q1-1984Q1-h quarters. The parameter ϕ is a hyperparameter and sets the degree of information given by the prior, small values corresponding to more informative priors. Several values of this parameter, delivering the best results, are considered in the empirical exercise. After model estimation we use 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 $\lambda_{i,h}$, to compute the individual forecasts of y_{t+h} as $\hat{y}^i_{t+h|t} = \widetilde{\lambda}^{'}_{i,h}w_{it}$. The BMA forecast is then given by $\hat{y}_{t+h|t} = \sum_{i=1}^{n} P(M_i/D)\hat{y}^i_{t+h|t}$.

- *Random walk (RW)*

  RW forecasts consists in taking $\hat{y}_{t+h|t} = y_t$ as the forecast of y_{t+h} for all h.

- *Philadelphia Survey of Professional Forecasters (SPF)*

  We consider the quarterly median forecasts of the Philadelphia SPF. Results with the mean are similar and will not be reported. These forecasts are the combination of the real-time projections of a panel of professional forecasters. The forecasts refer to the current quarter as well as to the following 4 quarters. SPF forecasts are extremely hard to beat when compared to standard benchmarks, see, e.g., Ang, Bakeart and Wei (2007), Stark (2010) or Faust and Wright (2012).

This list is certainly far from exhaustive and clearly short of the powerful methods that have proven useful for short-term forecasting and/or nowcasting. This includes, among others, methods that explore high-frequency data and/or mixed frequency data, see, e.g., Giannone, Reichlin and Small (2008), Clements and Galvão (2008, 2009) or Andreou et al. (2011). Now, very short term forecasting or nowcasting is clearly not the obvious match for the simple univariate low-pass filter or for the methods presented above, hence their consideration. An interesting extension that we leave for future research concerns combining powerful nowcasts (or simply SPF nowcasts) with low-pass filter forecasts for longer horizons.

4.3 Optimal Smoothing

An important practical question left to deal with concerns the specification of the cut-off period used in the low-frequency projections. Here we discuss how we choose the benchmark cut-off for each variable and horizon, giving useful guidelines to readily decide upon this filter design parameter in future empirical exercises. Clearly, the more we exclude (high) frequencies the more we will be giving up on the variance of the variable of interest, i.e., on potential forecast accuracy. On the other hand, attempts at fitting these high frequencies may lead to efficiency losses in small samples. This trade-off and, consequently, the optimal degree of smoothness, may vary with the data generating process and with the forecast horizon. Here we analyze pseudo out-of-sample forecasts obtained with the low-pass filter for various cut-off periods (following exactly the design described before). We do so for each variable and various forecast horizons. We let the cut-off period to vary from a minimum of 4 quarters (1 year) to a maximum of 48 quarters (12 years) in increments of 4 quarters. Then, we define the optimal cut-off period for each variable and forecast horizon as the cut-off period that minimizes the root mean square forecast error (RMSFE) in the period 1984Q1-2010Q4.

Table 2 shows the optimal degree of smoothness by forecast horizon for each variable. In general, larger forecast horizons are associated with a higher degree of smoothness. There are exceptions, such as with the industrial production index or the two inflation measures considered. In the case of the two inflation measures the optimal level is actually quite stable across horizons. But the

Table 2
Optimal cut-off period by forecast horizon for each variable. Evaluation period 1984Q1-2010Q4.

Group	**Variable**	**Forecast horizon** 1	2	4	6	8	12
BBC	Nominal output	8	12	12	12	20	28
	Unemployment rate	4	12	12	20	20	20
	Industrial production index	4	8	12	4	4	28
	3-Month treasury bill rate	8	8	16	16	16	20
	Real output	8	8	16	20	20	32
	Real Personal consumption expenditures	16	16	20	24	36	40
	Real private nonresidential fixed investment	8	12	12	12	12	20
	Real state & local cons. exp. & gross investment	20	20	20	20	20	36
BC	GDP deflator	16	28	28	28	28	28
	Housing starts	28	28	28	32	32	32
	Real private residential fixed investment	8	28	28	28	32	28
	Consumer price index	32	32	32	32	32	32
ABC	Real federal cons. exp. & gross investment	48	44	44	44	48	48

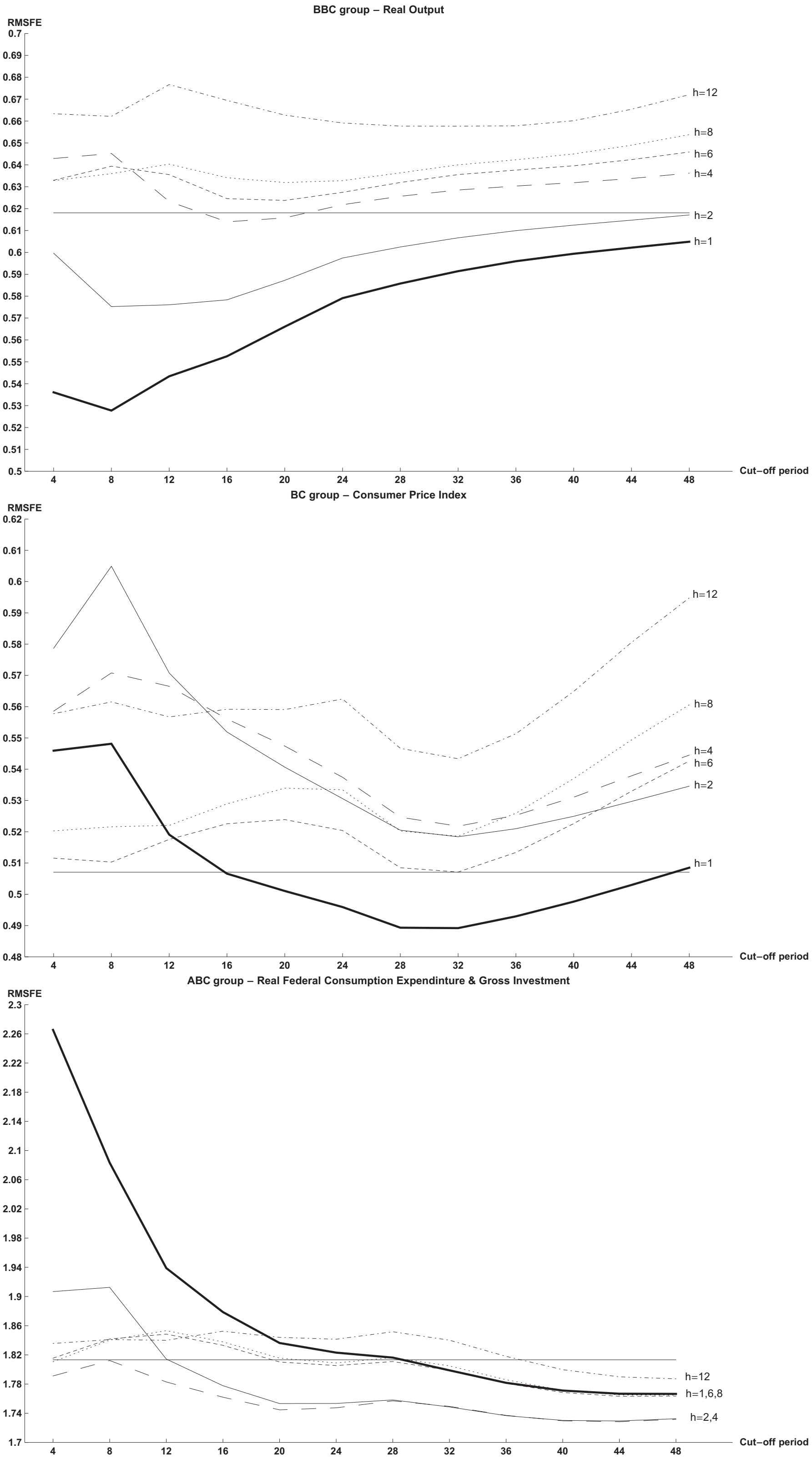
main conclusion is that the performance of the low-frequency filter-based forecasts is sensitive to the specification of the degree of smoothness whereas the optimal degree of smoothness generally grows, slowly, for forecast horizons larger than 2 quarters. This analysis suggests a rough classification of the variables, according to the optimal cut-off period, into three groups. The first group, denoted BBC (below business cycle), includes all variables with optimal cut-off period across forecast horizons most often below the standard business cycle cut-off period of 32 quarters. The BC (business cycle) group considers variables with optimal cut-off period in the vicinity of the typical business cycle cut-off period. The third group, denoted ABC (above business cycle), includes the variable (real federal spending) with optimal cut-off period above the typical business cycle cut-off period.[10] The first column of table 2 identifies the group of each variable. Our benchmark low-pass filter forecasts are based on the optimal cut-off periods presented in table 2.

Figure 1 presents individual panels for specific variables of each group and shows the RMSFE against different cut-off periods by forecast horizon. The figure makes visually clear the distinction between groups and the RMSFE behavior around the optimal cut-off period. We highlight that considering cut-off periods slightly above or below the optimal may not deteriorate significantly the accuracy of the forecasts. Still, it is clear that restricting the fluctuations of the variable that

[10]The optimal cut-off for this variable is often 48 (the largest value considered by us), but we have verified that larger values (up to 84 quarters) do not reduce the RMSFE for any horizon.

Figure 1

RMSFE against different cut-off periods by forecast horizon for a representative series of each group. Straight lines are the standard deviation of each variable considered. Evaluation sample: 1984Q1-2010Q4.



are approximated is relevant for the accuracy of the forecasts. We will come back to this issue when discussing the empirical results. In order to tackle obvious criticisms regarding the hindsight embodied in this choice we will carefully analyze low-pass filter forecasts based on sub-optimal cut-offs in the vicinity of the optimal (specifically, plus or minus 4 quarters). Further, we will also look at filter forecasts with cut-off period determined as the optimum over the sample 1974Q1-1983Q4 (i.e., before the evaluation period) as well as over other post 1974 sub-samples.

4.4 Results

To compare the performance of the different models and methods we analyze the RMSFE of each competing forecast relative to that of the low-pass filter (LPF) forecasts. Table 3 summarizes the results by variable and forecast horizon considering as evaluation period 1984Q1- 2010Q4. Ratios above one mean that the LPF forecasts outperform the alternative forecast in the mean squared forecast error sense. In panel (A) competing forecasts are compared to the low-pass filter with optimal cut-off period while in panels (B) and (C) they are compared to low-pass filter forecasts using a sub-optimal cut-off period; specifically, the optimal cut-off minus 4 quarters in panel (B) and plus 4 quarters in panel (C). When the optimal cut-off period is 4 quarters RMSFE ratios are not reported in panel (B). For each variable, the first line reports the RMSFE of the benchmark forecast while the remaining lines report the RMSFE ratios. We also run the following regression:

$$y_{t+h} = \alpha + \beta_0 \widehat{y}_{t+h}^{Low} + \beta_1 \widehat{y}_{t+h}^{m} + \varepsilon_{t+h} \tag{4}$$

after Fair and Shiller (1989), where y_{t+h} is the observation of the forecasted variable, $\widehat{y}_{t+h}^{Low}$ is the forecast obtained with the low-pass filter, $\widehat{y}_{t+h}^{m}$ is the forecast from model/method m and ε_{t+h} is a (most likely serially correlated) regression error. Obviously, if $\beta_1 \neq 0$, then forecasts using model m add information relative to the low-pass filter and to the constant term. We include a star close to the rel. RMSFE if the null of forecast encompassing ($\beta_1 = 0$) is rejected at 5%. We apply the small sample correction from Harvey, Leybourne and Newbold (1998).[11] The main conclusions follow:

- We start by noting that SPF forecasts are extremely hard to beat when $h = 1, 2$. Allow us

[11] Results with Newey-West robust standard errors are qualitatively similar.

to recall the fact that SPF panelists have a slight informational advantage as their forecasts incorporate information until approximately the middle of each quarter in which the forecast is made whereas our pseudo-out-of-sample design implies that we use information referring to the end of the previous quarter and before, although often available only at the middle of the quarter. The informational advantage of the SPF is specially acute, and reflected in the results, for 3-month treasury bill rate (which is released without delays), CPI inflation, industrial production index, unemployment rate and housing starts (SPF panelists know the figures for the first month of each quarter).[12]

- With very few exceptions, LPF forecasts systematically outperform the other methods, for all horizons and even using a sub-optimal cut-off period in the cases of nominal output, real state and local government spending, real federal government spending, GDP deflator, consumer price index and housing starts. Vis-a-vis the best alternative methods, the gains are quite substantial for both measures of inflation as well as for nominal output. For the two series related to government spending and housing starts the gains are systematic but less pronounced.

- Moreover, LPF forecasts with optimal cut-off period also systematically outperform the other methods, for all horizons, in the case of the unemployment rate and 3-month treasury bill rate. In these cases, deviating from the optimal cut-off period implies loosing the lead in a few instances, concentrated at short horizons ($h = 1, 2$ and sometimes $h = 4, 6$).

- For industrial production at $h = 6, 8, 12$ and private investment (residential) at $h = 4, 6, 8, 12$ LPF forecasts with optimal cut-off period also outperform the other methods. This lead is generally maintained if one moves away from the optimal cut-off period.

- For real personal consumption expenditures, non-residential private investment and real output LPF forecasts performs less well. In any case, they are still superior to all the other methods in some instances when $h = 4, 6, 8$ but this lead is sensitive to the choice of cut-off period. Deviations from the optimal level imply loosing the lead in various instances.

[12] The informational/timing advantage is slim for national accounts related series since they are released for the first time with a lag of half a quarter. However, other relevant information available up to the middle of the quarter is surely incorporated by SPF panelists. Again, we could use SPF projections or powerful nowcasting methods as the starting point (or final observation of y_t) for all methods. This would surely "control" for these informational advantages but make unclear the sources of differences in forecast accuracy across the methods presented.

- Focusing now on the other methods, there is no clear pattern regarding forecast accuracy. The simple iterated autoregression forecasts (IAR) usually outperform the direct autoregression (DAR) and perform well in comparison with the other methods, specially in the case of real output at long horizons, real personal consumption expenditures for most horizons (actually the best method overall), private investment (residential and non-residential), housing starts and real federal spending. As for the remaining methods, we note the good results obtained with the best Bayesian model averaging (BMA) configuration and also with EWA. Still, the use of a large dataset (in these and the other methods using it, FAAR and FAVAR) does not result in relevant improvements and fails almost always in producing forecasts more accurate than the simple LPF forecasts.

- Regarding the forecast encompassing test, we note that it does not contradict the main conclusions above. Only in the case of private fixed investment (residential and non-residential) and GDP inflation at short horizons do we reject the null of encompassing in several cases, despite the fact that the rel. RMSFE is in general well above 1 in the latter case.

All in all, the value-added of low-pass filter based forecasts seems unquestionable. Forecast gains vis-a-vis several statistical methods are a systematic feature and can be quite substantial whereas the losses are most often trivial.

To investigate whether these results are conditional on the available sample or evaluation period we have repeated the analysis under different settings.[13] The variations considered include estimation with only post-1984 data and evaluation in various post-1984 sub-periods. The main conclusions drawn here remain valid. Below we analyze more deeply the robustness of the results to the most critical design feature of the LPF, i.e., the cut-off period defining low and high frequencies.

[13]Results are available upon request.

Table 3

Relative RMSFEs by variable and forecast horizon. Evaluation period: 1984Q1-2010Q4

	(A) Optimal cut-off						*(B) Optimal cut-off minus 4 quarters*						*(C) Optimal cut-off plus 4 quarters*					
	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
Nominal Output																		
LPF (RMSFE)	0.5613	0.6152	0.6634	0.6888	0.7092	0.7808	0.5736	0.6294	0.7016	0.7063	0.7157	0.7876	0.5705	0.6253	0.6645	0.6894	0.7192	0.7810
IAR	1.185*	1.219	1.252	1.300	1.307	1.238	1.160*	1.191*	1.184*	1.268*	1.295	1.227*	1.166	1.199	1.250	1.299	1.289*	1.238
DAR	1.185*	1.209	1.226	1.235	1.175	1.281	1.160*	1.182*	1.159*	1.204*	1.164	1.270*	1.166	1.190	1.224	1.234	1.158	1.281
FAAR	1.135*	1.193	1.148	1.174	1.144	1.349	1.110*	1.166	1.086	1.144	1.133	1.337*	1.116*	1.173	1.146	1.172	1.128	1.348
FAVAR	1.141*	1.198	1.257	1.253	1.211	1.148	1.116*	1.171	1.189	1.222	1.200	1.138*	1.122*	1.178	1.255	1.252	1.194	1.147
EWA	1.170*	1.178	1.194	1.211	1.149	1.260	1.145*	1.151*	1.129*	1.181	1.139	1.249*	1.151*	1.159	1.192	1.210	1.133	1.259
BMA(20)	1.041*	1.136	1.149	1.125	1.102	1.209	1.019*	1.110*	1.087	1.097	1.093	1.199*	1.024*	1.118	1.147	1.124	1.087	1.209
BMA(5)	1.009*	1.127	1.173	1.140	1.112	1.211	0.988*	1.102*	1.109	1.112	1.102	1.200*	0.993*	1.109	1.171	1.139	1.096	1.210
BMA(2)	1.001*	1.135*	1.221	1.187	1.142	1.227	0.979*	1.109*	1.154	1.157	1.132	1.217*	0.985*	1.116*	1.219	1.185	1.126	1.227
RW	1.161	1.145*	1.247	1.362	1.409	1.288	1.136	1.119*	1.179*	1.328	1.396	1.277	1.142	1.127*	1.245	1.361	1.389	1.288
SPF	**0.829***	**0.914***	**0.988**	-	-	-	**0.811***	**0.894***	**0.934**	-	-	-	**0.816***	**0.900***	**0.987**	-	-	-
Unemployment Rate																		
LPF (RMSFE)	0.1920	0.2417	0.2794	0.2826	0.2818	0.2815	-	0.2424	0.2928	0.2857	0.2854	0.2885	0.2012	0.2500	0.2812	0.2886	0.2871	0.2842
IAR	1.033	1.026	1.093*	1.071	1.049	1.047	-	1.026	1.043*	1.059	1.036*	1.021	0.986*	0.995*	1.087	1.048*	1.030*	1.037*
DAR	1.033	1.032	1.112*	1.073	1.081	1.105	-	1.026	1.062*	1.061	1.067	1.078	0.986*	0.998*	1.106	1.050	1.061	1.095
FAAR	0.970*	1.042	**0.980**	**0.977***	1.050	1.119	-	1.039	0.935	**0.966**	1.036	1.092	0.926*	1.008	**0.974**	**0.957**	1.030	1.108
FAVAR	0.957*	1.034*	1.121	1.150	1.140	1.136*	-	1.031	1.070	1.137	1.125	1.108	0.913*	0.999	1.114	1.126	1.119	1.125*
EWA	1.012	1.015*	1.070	1.053	1.065	1.084	-	1.012	1.021	1.041	1.051	1.057	0.966*	0.981*	1.063	1.031	1.045	1.073
BMA(20)	1.014*	1.177	1.045	1.089	1.066	1.147	-	1.173	0.998	1.077	1.052	1.119	0.968*	1.138	1.039	1.066	1.046	1.136
BMA(5)	1.009	1.147	1.061	1.056	1.050	1.089	-	1.144	1.013	1.044	1.037	1.063	0.963*	1.109	1.055	1.033	1.031	1.079
BMA(2)	1.020	1.120	1.095	1.037	1.043	1.053	-	1.117	1.045	1.026	1.029	1.028	0.973*	1.083	1.088	1.015	1.023	1.043
BMA(1)	1.048	1.118	1.143	1.052	1.049	1.060	-	1.115	1.091	1.041	1.036	1.034	1.000*	1.081*	1.136	1.030	1.030	1.050
RW	1.081	1.105*	1.313	1.472	1.529	1.488	-	1.101*	1.253	1.455	1.510	1.452	1.032*	1.068*	1.305	1.441	1.501	1.474
SPF	**0.710***	**0.917***	0.995*	-	-	-	-	**0.914***	0.949*	-	-	-	**0.677***	**0.887***	0.989*	-	-	-
Industrial Production Index																		
LPF (RMSFE)	0.9017	1.1627	1.2923	1.2658	1.2658	1.2613	-	1.2331	1.3147	-	-	1.2634	0.9313	1.1995	1.3158	1.2754	1.2669	1.2637
IAR	0.980*	1.015	0.984	1.008	1.008	1.012	-	0.954*	0.967	-	-	1.010	0.949*	0.984	0.966	1.000	1.007	1.010
DAR	0.980*	1.011	0.977	1.039	1.031	1.053	-	0.954*	0.960	-	-	1.052	0.949*	0.980	0.959	1.032	1.030	1.051
FAAR	1.079*	1.074	0.985*	1.064	1.048	1.293	-	1.012	0.968	-	-	1.291	1.044*	1.041	0.967*	1.056	1.047	1.291
FAVAR	1.114*	1.076	1.019*	1.097	1.078	1.069	-	1.015	1.002	-	-	1.068	1.079*	1.043	1.001	1.089	1.077	1.067
EWA	0.967*	0.995	**0.955***	1.039	1.033	1.049	-	0.938*	**0.939**	-	-	1.048	0.936*	0.965*	**0.938***	1.031	1.032	1.047
BMA(20)	0.997*	1.137	1.006	1.051	1.043	1.101	-	1.072	0.989	-	-	1.099	0.965*	1.102	0.988	1.043	1.042	1.099
BMA(5)	0.985*	1.136	1.029	1.046	1.048	1.080	-	1.071	1.011	-	-	1.078	0.954*	1.101	1.010	1.038	1.047	1.078
RW	1.017*	1.158	1.361	1.554	1.466	1.324	-	1.091	1.338	-	-	1.322	0.985*	1.122	1.337	1.542	1.465	1.322
SPF	**0.961***	**0.981**	1.004	-	-	-	-	**0.925**	0.986	-	-	-	**0.931***	**0.951**	0.986	-	-	-

(continued)

	(A) *Optimal cut-off*						(B) *Optimal cut-off minus 4 quarters*						(C) *Optimal cut-off plus 4 quarters*					
	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
3-Month Treasury Bill Rate																		
LPF (RMSFE)	0.4066	0.4555	0.4817	0.4835	0.4826	0.4799	0.4199	0.5035	0.4898	0.4932	0.4937	0.4828	0.4299	0.4653	0.4894	0.4878	0.4832	0.4921
IAR	1.128	1.155	1.009	1.030*	1.009	1.067	1.092	1.045*	**0.993**	1.010	**0.986**	1.061	1.067	1.131	**0.993**	1.021*	1.007	1.040
DAR	1.128	1.206	1.021	1.031	1.062	1.128	1.092	1.091*	1.004	1.011	1.038	1.121	1.067	1.181	1.005	1.022	1.060	1.100
FAAR	1.234	1.315	1.063	1.144	1.080	1.515	1.194	1.189	1.045	1.121	1.055	1.506	1.167	1.287	1.046	1.134	1.078	1.478
FAVAR	1.072	1.036	1.027*	1.027	1.013	1.020	1.038	0.937*	1.011*	1.006	0.990	1.014	1.014*	1.014	1.011*	1.018	1.011*	**0.995**
EWA	1.091	1.182	1.026	1.026	1.064	1.166	1.057	1.069	1.009	1.006	1.040	1.160	1.032*	1.157	1.010	1.017	1.063	1.137
BMA(2)	1.042*	1.129	1.014	1.045	1.059	1.109	1.009	1.021	0.997	1.025	1.035	1.103	0.986*	1.105	0.998	1.036	1.058	1.082
BMA(1)	1.021*	1.085	1.013	1.041	1.058	1.118	0.988*	0.982	0.997	1.020	1.035	1.112	0.965*	1.062	0.997	1.032	1.057	1.091
BMA(0.5)	1.027*	1.066	1.019	1.050	1.071	1.179	0.994	0.964	1.003	1.030	1.047	1.172	0.971*	1.043	1.003	1.041	1.070	1.150
RW	1.082*	1.210	1.326	1.581	1.728	1.684	1.048*	1.095*	1.304	1.549	1.689	1.674	1.023*	1.185	1.305	1.566	1.726*	1.642
SPF	**0.387***	**0.953***	1.056	-	-	-	**0.374***	**0.862***	1.039	-	-	-	**0.366***	**0.932***	1.039	-	-	-
Real Output																		
LPF (RMSFE)	0.5277	0.5752	0.6140	0.6237	0.6319	0.6577	0.5361	0.5996	0.6232	0.6246	0.6341	0.6577	0.5434	0.5761	0.6158	0.6274	0.6328	0.6578
IAR	1.020	1.005	1.011	1.005	**0.994**	**0.952***	1.004*	0.964*	0.996	1.004	**0.991**	**0.952***	0.991*	1.004	1.008	**0.999**	**0.993**	**0.952***
DAR	1.020	1.011	1.053	1.056	1.013	0.986	1.004*	0.970	1.038	1.055	1.009	0.986	0.991*	1.010	1.050	1.050	1.011	0.985
FAAR	1.063*	1.135	1.034	1.027	1.021	1.033	1.047*	1.089	1.018	1.026	1.017	1.033	1.033*	1.134	1.031	1.021	1.019	1.033
FAVAR	1.035*	1.082	1.152	1.123	1.069	1.003*	1.019*	1.038	1.135	1.122	1.066	1.003	1.005*	1.081	1.148	1.117	1.068	1.002*
EWA	1.000*	0.997	1.042	1.052	1.010	0.981	0.984*	0.956	1.026	1.051	1.006	0.981	0.971*	0.996	1.039	1.046	1.008	0.981
BMA(20)	1.029*	1.067	1.068	1.018	1.017	0.980	1.013*	1.023	1.052	1.016	1.014	0.980	0.999*	1.065	1.064	1.012	1.016	0.980
BMA(5)	1.005*	1.070	1.100	1.027	1.016	0.996	0.989*	1.027	1.084	1.026	1.013	0.996	0.976*	1.069	1.097	1.021	1.015	0.996
BMA(2)	0.999*	1.119	1.178	1.067	1.043	1.057	0.984*	1.074	1.161	1.066	1.039	1.057	0.971*	1.118*	1.175	1.061	1.042	1.057
RW	1.197	1.127*	1.314	1.419	1.490	1.478	1.179	1.081*	1.295	1.417	1.484	1.478	1.163	1.125*	1.310	1.410	1.488	1.477
SPF	**0.911***	**0.950***	1.004	-	-	-	**0.897***	**0.912***	**0.989**	-	-	-	**0.885***	**0.949**	1.001	-	-	-
Real Personal Consumption Expenditures																		
LPF (RMSFE)	0.4767	0.4860	0.5325	0.5542	0.5729	0.6098	0.4773	0.4895	0.5365	0.5549	0.5744	0.6102	0.4849	0.4923	0.5366	0.5552	0.5741	0.6144
IAR	0.996	**0.994**	1.016	**0.995**	**0.976**	**0.921***	0.995	**0.987**	1.009	**0.994**	**0.973**	**0.921***	0.979*	**0.981***	1.009	**0.993**	**0.974**	**0.914***
DAR	0.996	1.006	1.063	1.069	1.047	0.956	0.995	0.999	1.055	1.068	1.045	0.956	0.979*	0.993	1.055	1.068	1.045	0.949
FAAR	1.212*	1.164	1.167	1.089	1.051	1.210	1.211*	1.155	1.158	1.088	1.048	1.209	1.192*	1.148	1.158	1.087	1.049	1.201
FAVAR	1.229*	1.375	1.267	1.113	1.039*	0.977*	1.228*	1.365	1.257	1.112	1.036*	0.977*	1.209*	1.357	1.257	1.111	1.037*	0.970*
EWA	0.995*	1.016	1.075	1.071	1.049	0.953	0.994	1.008	1.067	1.070	1.046	0.952	0.978*	1.002	1.067	1.069	1.046	0.946
BMA(20)	1.024*	1.061	1.113	1.069	1.072	1.044	1.023*	1.054	1.105	1.068	1.069	1.044	1.007*	1.048	1.105	1.067	1.069	1.037
BMA(5)	1.023*	1.075	1.109	1.062	1.074	1.040	1.021*	1.068	1.100	1.061	1.071	1.039	1.005*	1.062	1.100	1.060	1.072	1.032
RW	1.295	1.244	1.295	1.232*	1.285	1.283	1.293	1.235	1.285	1.231*	1.282	1.283	1.273	1.228	1.285	1.230*	1.282	1.274
SPF	**0.935***	1.003*	1.041	-	-	-	**0.934***	0.995*	1.033	-	-	-	**0.919***	0.990*	1.033	-	-	-

(continued)

Model	(A) Optimal cut-off						(B) Optimal cut-off minus 4 quarters						(C) Optimal cut-off plus 4 quarters					
	Forecast horizon						Forecast horizon						Forecast horizon					
	1	2	4	6	8	12	1	2	4	6	8	12	1	2	4	6	8	12
Real Private Nonresidential Fixed Investment																		
LPF (RMSFE)	1.8892	2.0969	2.2923	2.3441	2.3466	2.3619	2.0021	2.1089	2.3793	2.3872	2.3878	2.4183	1.9346	2.2109	2.3651	2.3997	2.3910	2.3851
IAR	1.019	1.010	1.023	1.019*	1.010	**0.997**	0.962*	1.004	0.985	1.001*	0.993	**0.974**	0.995	0.958*	0.991	**0.995***	0.991	**0.987**
DAR	1.019	0.990	1.008	1.020	1.009	1.028	0.962*	0.984	0.971*	1.002	**0.991**	1.004	0.995	0.939*	0.977	0.997	**0.990**	1.018
FAAR	0.959*	0.949	0.993	1.051	1.063	1.008	0.905*	0.943*	0.957	1.032*	1.045	0.984	0.936*	0.900	0.963	1.026	1.044	0.998
FAVAR	0.938*	0.965	1.032	1.025	1.030	1.038	0.885*	0.960	0.995	1.007	1.012	1.014	0.916*	0.915	1.001	1.001	1.011	1.028
EWA	0.991	0.970*	0.996	1.023	1.011	1.011	0.935*	0.964*	0.960*	1.005	0.993	0.987	0.968*	0.920*	0.965	1.000	0.992	1.001
BMA(20)	0.944*	0.967*	0.986	1.057	1.039	1.243	0.891*	0.961*	0.950	1.038	1.021	1.214	0.922*	0.917*	0.956	1.032	1.019	1.231
BMA(5)	0.947*	0.967*	0.998	1.043	1.022	1.178	0.893*	0.961*	0.961	1.024	1.004	1.150	0.925*	0.917*	0.967	1.019	1.003	1.166
BMA(2)	0.959*	0.984*	1.036	1.055	1.034	1.113	0.904*	0.978*	0.998	1.036	1.016	1.087	0.936*	0.933*	1.004	1.030	1.014	1.102
RW	1.146	1.173*	1.314	1.508	1.509	1.407	1.082*	1.166*	1.266*	1.481	1.483*	1.374	1.119	1.112*	1.273*	1.473	1.481	1.393
SPF	**0.860***	**0.914***	**0.958***	-	-	-	**0.811***	**0.909***	**0.923***	-	-	-	**0.839***	**0.867***	**0.929***	-	-	-
Real State & Local Consumption Expenditure & Gross Investment																		
LPF (RMSFE)	0.5777	0.6029	0.6391	0.6557	0.6738	0.6978	0.5828	0.6137	0.6595	0.6785	0.6965	0.7024	0.5979	0.6213	0.6552	0.6702	0.6857	0.6978
IAR	1.062	1.067*	1.046*	1.049	1.029	1.005	1.053	1.048	1.014	1.013	**0.995**	0.999	1.026	1.035	1.020	1.026	1.011	1.005*
DAR	1.062	1.067	1.051*	1.081	1.085	1.101	1.053	1.048	1.018	1.044	1.049*	1.094	1.026	1.035	1.025	1.057	1.066	1.101
FAAR	1.119	1.144	1.066	1.032	1.166	**0.994**	1.109	1.124	1.033	**0.997**	1.128	**0.987**	1.081	1.110	1.040	1.010	1.146	**0.994**
FAVAR	1.149	1.175	1.166	1.152	1.133	1.117	1.139	1.155	1.130	1.113	1.096	1.110	1.110	1.141	1.137	1.127	1.113	1.117
EWA	1.060	1.063	1.028	1.056	1.077	1.091	1.051	1.044	0.996	1.021	1.042	1.084	1.024	1.032	1.003	1.034	1.058	1.091
BMA(20)	1.073	1.089	1.004	1.069	1.171	1.065	1.063	1.070	**0.973**	1.033	1.133	1.058	1.036	1.056	**0.979**	1.046	1.151	1.065
RW	1.197	1.204	1.277	1.272	1.271	1.382	1.186	1.183	1.237	1.229	1.230	1.373	1.156	1.169*	1.245	1.244	1.249	1.382
SPF	1.061*	1.028*	1.066	-	-	-	1.052*	1.010*	1.033	-	-	-	1.025*	**0.997***	1.040	-	-	-
GDP Deflator																		
LPF (RMSFE)	0.2182	0.2297	0.2357	0.2557	0.2661	0.3020	0.2218	0.2302	0.2371	0.2584	0.2707	0.3113	0.2203	0.2340	0.2407	0.2603	0.2700	0.3034
IAR	1.109	1.159*	1.322*	1.518	1.687	1.851	1.091	1.156	1.315*	1.501	1.659	1.796	1.098	1.138*	1.295*	1.491	1.663	1.843
DAR	1.109	1.169*	1.466*	1.839	2.111	2.313	1.091	1.166*	1.457*	1.820	2.076	2.244	1.098	1.147*	1.435*	1.807	2.081	2.302
FAAR	1.142*	1.254*	1.625	1.733	1.715	2.058	1.124*	1.251*	1.616	1.715	1.686	1.997	1.131*	1.231*	1.592	1.703	1.690	2.049
FAVAR	1.287	1.438*	1.677*	1.886	2.093	2.307	1.266	1.435*	1.668*	1.866	2.057	2.238	1.274	1.411*	1.643	1.852	2.063	2.296
EWA	1.083	1.137*	1.391*	1.718*	1.956	2.200	1.065	1.135*	1.384*	1.700*	1.922	2.135	1.072*	1.116*	1.363*	1.688	1.927	2.190
BMA(20)	1.110*	1.078*	1.357*	1.723*	2.034	2.167	1.092*	1.076*	1.349*	1.705*	1.999	2.103	1.099*	1.058*	1.329*	1.693	2.004	2.157
BMA(5)	1.099*	1.084*	1.401*	1.799*	1.900	1.422	1.081*	1.081*	1.393*	1.780*	1.868	1.380	1.088*	1.064*	1.372*	1.767	1.873	1.416
BMA(2)	1.092*	1.117*	1.494*	1.916	1.730	1.049	1.074*	1.115*	1.485*	1.896	1.701	1.018	1.082*	1.097*	1.463*	1.882	1.705	1.044
BMA(0.5)	1.124	1.231*	1.726	2.227	1.466	2.610	1.106	1.229*	1.716	2.203	1.441	2.533	1.113*	1.209*	1.690	2.187	1.445	2.598
RW	1.211	1.221	1.130*	1.186	1.190	1.378	1.191	1.219	1.124*	1.174	1.170	1.337	1.199	1.199	1.107*	1.165	1.173	1.371
SPF	1.048*	1.108*	1.304	-	-	-	1.031*	1.105*	1.296	-	-	-	1.038*	1.087*	1.277	-	-	-

(continued)

Model	(A) Optimal cut-off						(B) Optimal cut-off minus 4 quarters						(C) Optimal cut-off plus 4 quarters					
	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)	6.5293	6.6253	6.6839	6.6777	6.6812	6.6925	6.5605	6.6790	6.7590	6.6777	6.6884	6.6954	6.5552	6.6368	6.6860	6.7094	6.7094	6.7204
IAR	1.051	1.045	1.037*	1.026*	1.023	1.024	1.046	1.037	1.026*	1.026*	1.021	1.024	1.047	1.043	1.037*	1.021*	1.018	1.020
DAR	1.051	1.043	1.043	1.052	1.104	1.107	1.046	1.034	1.031	1.052	1.103*	1.106	1.047	1.041	1.043	1.047	1.100	1.102
FAAR	1.219	1.100*	1.020	1.075	1.082	1.208	1.213	1.092*	1.008	1.075	1.081	1.208	1.214	1.099	1.019	1.069	1.078	1.203
FAVAR	1.268	1.232*	1.097	1.044	1.041	1.032	1.262	1.222*	1.085	1.044	1.040	1.031	1.263	1.230*	1.097	1.039	1.037	1.027
EWA	1.042	1.018	1.025	1.042	1.095	1.112	1.038	1.010*	1.014	1.042	1.094	1.111	1.038	1.016	1.025	1.037	1.091	1.107
BMA(20)	1.072	1.034	1.024	1.038	1.094	1.129	1.067	1.025*	1.013	1.038	1.093	1.129	1.068	1.032	1.024	1.033	1.089	1.125
BMA(5)	1.054	1.023*	1.015*	1.022	1.092	1.140	1.049	1.015*	1.004	1.022	1.091	1.139	1.050	1.022*	1.015*	1.017*	1.087	1.135
BMA(2)	1.041	1.019*	1.009*	1.009*	1.098	1.172	1.036	1.010*	0.997*	1.009	1.097	1.171	1.037	1.017*	1.008*	1.004*	1.094	1.167
BMA(1)	1.045	1.025*	1.007*	1.005	1.116	1.219	1.040	1.016*	**0.996***	1.005	1.114	1.219	1.041	1.023*	1.007*	1.000	1.111	1.214
RW	1.280	1.314	1.427	1.489	1.417	1.427	1.274	1.303	1.411	1.489	1.416	1.427	1.275	1.311	1.427	1.482	1.412	1.421
SPF	**0.750***	**0.988***	1.109	-	-	-	**0.746***	**0.980***	1.097	-	-	-	**0.747***	**0.986***	1.109	-	-	-
Real Private Residential Fixed Investment																		
LPF (RMSFE)	2.7526	3.0661	3.2042	3.2489	3.2724	3.2662	2.7919	3.1243	3.2974	3.3531	3.2760	3.3608	2.9444	3.0956	3.2123	3.2515	3.3199	3.2664
IAR	0.969	0.996*	1.093	1.081	1.063	1.064	0.955*	0.978*	1.062	1.047	1.061	1.034*	0.906*	0.987*	1.090	1.080	1.047	1.064
DAR	0.969	0.987*	1.106	1.132	1.208	1.251	0.955*	0.969*	1.075	1.097	1.207	1.216	0.906*	0.978*	1.103	1.131	1.191	1.251
FAAR	1.278	1.196*	1.181*	1.063	1.130	1.481	1.260*	1.174*	1.147*	1.030	1.129	1.439	1.195*	1.185*	1.178*	1.062	1.114	1.481
FAVAR	1.314	1.420*	1.330*	1.205	1.134	1.106	1.296*	1.394*	1.293*	1.168	1.132	1.074	1.229*	1.407*	1.327*	1.204	1.117	1.105
EWA	0.953*	0.950*	1.073*	1.111	1.190	1.263	0.940*	0.932*	1.042	1.077	1.189	1.228	0.891*	0.941*	1.070*	1.110	1.173	1.263
BMA(5)	0.888*	0.984*	1.068*	1.076	1.181	1.477	0.875*	0.966*	1.038*	1.042	1.180	1.436	0.830*	0.975*	1.066*	1.075	1.164	1.477
BMA(2)	0.870*	0.983*	1.060*	1.052	1.191	1.338	0.858*	0.965*	1.030*	1.019	1.189	1.300	0.814*	0.974*	1.057*	1.051	1.174	1.338
BMA(1)	0.878*	1.001*	1.079*	1.036	1.212	1.326	0.865*	0.983*	1.049*	1.004	1.210	1.288	0.820*	0.992*	1.076*	1.035	1.194	1.326
BMA(0.5)	0.913*	1.038*	1.120	1.027	1.241	1.364	0.900*	1.018*	1.088	**0.995**	1.239	1.325	0.854*	1.028*	1.117	1.027	1.223	1.363
RW	1.058*	1.086*	1.365	1.393	1.413	1.533	1.043*	1.066*	1.326	1.350	1.411	1.490	0.989*	1.076*	1.361	1.392	1.393	1.533
SPF	**0.779***	**0.909***	1.033	-	-	-	**0.768***	**0.892***	1.004	-	-	-	**0.728***	**0.900***	1.030*	-	-	-
Consumer Price Index																		
LPF	0.4892	0.5184	0.5218	0.5071	0.5186	0.5434	0.4893	0.5205	0.5247	0.5085	0.5202	0.5467	0.4929	0.5210	0.5253	0.5134	0.5259	0.5513
IAR	1.156	1.199	1.255	1.289	1.357	1.452	1.156	1.194	1.249	1.285	1.353	1.444*	1.147	1.193	1.247	1.273	1.338	1.431
DAR	1.156	1.204	1.329	1.457	1.597	1.746	1.156	1.199	1.322	1.453	1.592*	1.735	1.147	1.198	1.320	1.440	1.574	1.720
FAAR	1.213	1.291	1.321	1.481	1.441	2.385	1.212	1.286	1.314	1.477	1.436	2.370	1.204*	1.285	1.312	1.463	1.421	2.350
FAVAR	1.170	1.229	1.224	1.317	1.397	1.509	1.170	1.224	1.217	1.313	1.393	1.500	1.161	1.222	1.216	1.301	1.378	1.487
EWA	1.147	1.192	1.268	1.399	1.518	1.715	1.146	1.188	1.261	1.395	1.513*	1.705	1.138	1.186	1.260	1.382	1.497	1.691
BMA(2)	1.126	1.206	1.218	1.089	1.292	1.432	1.126	1.201	1.211	1.086	1.288	1.423	1.117	1.200	1.210	1.076	1.274	1.411
BMA(1)	1.122	1.236	1.227	1.065	1.132	1.087	1.122	1.231	1.220	1.062	1.129	1.081	1.113	1.230	1.219	1.052	1.116	1.072
BMA(0.5)	1.132	1.283	1.251	1.150	1.056	**0.998**	1.132	1.278	1.245	1.147	1.053	**0.992**	1.124	1.276	1.243	1.136	1.041	**0.984**
RW	1.238	1.343	1.371*	1.292	1.296	1.254	1.237	1.338	1.364*	1.289	1.292	1.246	1.228	1.337	1.362	1.276	1.278	1.236
SPF	**0.579***	**0.903***	**0.940***	-	-	-	**0.578***	**0.899***	**0.935***	-	-	-	**0.574***	**0.898***	**0.934***	-	-	-

(continued)

Model	*(A) Optimal cut-off* Forecast horizon 1	2	4	6	8	12	*(B) Optimal cut-off minus 4 quarters* Forecast horizon 1	2	4	6	8	12	*(C) Optimal cut-off plus 4 quarters* Forecast horizon 1	2	4	6	8	12
Real Federal Consumption Expenditures & Gross Investment																		
LPF (RMSFE)	1.7665	1.7294	1.7284	1.7632	1.7647	1.7872	1.7667	1.7302	1.7296	1.7684	1.7650	1.7899	1.7687	1.7325	1.7316	1.7635	1.7682	1.7890
IAR	0.994*	1.010*	1.047	1.035	1.038	1.034	0.994*	1.009*	1.046	1.032	1.038	1.033	0.993*	1.008*	1.045	1.035	1.036	1.033
DAR	0.994*	1.014*	1.047	1.055	1.059	1.058*	0.994*	1.013*	1.047	1.052	1.059	1.057*	0.993*	1.012*	1.045	1.055	1.057	1.057*
FAAR	1.032*	1.038*	1.072	1.079	1.111	1.121	1.032*	1.037*	1.071	1.076	1.111	1.119	1.031*	1.036*	1.070	1.079	1.109	1.120
FAVAR	1.076	1.073	1.079	1.074	1.058	1.050	1.076	1.073	1.078	1.071	1.058	1.048	1.075	1.071	1.077	1.074	1.056	1.049
EWA	1.001*	1.017*	1.044	1.057	1.054	1.057*	1.001*	1.017*	1.043	1.054	1.053	1.056*	1.000*	1.015*	1.042	1.057	1.051	1.056*
BMA(5)	0.994*	1.002*	1.031	1.041*	1.049	1.027	0.994*	1.002*	1.030	1.038	1.049	1.026	0.992*	1.000*	1.029	1.041*	1.047	1.026
BMA(2)	0.990	1.000*	1.037	1.044*	1.028	1.019	0.990	1.000*	1.036	1.041	1.028	1.018	0.989	0.998*	1.035	1.044	1.026	1.018
RW	1.532*	1.440	1.326	1.378	1.342	1.316	1.532*	1.439	1.325	1.374	1.341	1.314	1.530*	1.437	1.323	1.378	1.339	1.315
SPF	**0.933***	**0.944***	**0.940***	-	-	-	**0.933***	**0.944***	**0.939***	-	-	-	**0.932***	**0.942***	**0.938***	-	-	-

Notes: For each indicator/variable, the first line of the table reports the RMSFE obtained with the low-pass filter (LPF) while all the other entries report the relative RMSFEs, i.e., the RMSFEs of the forecasts of each method relative to the RMSFE obtained with LPF. All ratios below one are highlighted in grey and the values in bold represent the smallest relative RMSFE by column, but only those below 1. In panel *(A)* alternative forecasts are compared to the optimal cut-off LPF forecasts. In panels *(B)* and *(C)* alternative forecasts are compared to LPF forecasts using a cut-off period equal to the optimal minus or plus 4 quarters, respectively. The estimation sample starts always in 1959Q2 and the evaluation period is 1984Q1-2010Q4. For BMA forecasts the number in parenthesis is the hyperparameter ϕ described in the text. A star close to the rel. RMSFE indicates that the null of forecast encompassing ($\beta_1 = 0$) is rejected at 5%. We apply the small sample correction in Harvey, Leybourne and Newbold (1998).

4.4.1 Robustness - Cut-off Period

Table 4 presents the optimal cut-off period determined over various sub-samples: 1974Q1-1983Q4 (i.e., with data available before our benchmark evaluation period), 1974Q1-1990Q4, 1974Q1-2000Q4 and also 1984Q1-2010Q4 (results already presented in section 4.3, table 2, and repeated here only for comparison). Again, we let the cut-off period to vary from a minimum of 4 quarters to a maximum of 48 quarters (12 years) in increments of 4 quarters. Yet again, the estimation sample begins always in 1959Q2 and we define the optimal cut-off period for each variable and forecast horizon as the cut-off minimizing the RMSFE in each sample. Table 5 reports the RMSFE ratios implied by these cut-off periods when they are applied in the benchmark evaluation period, 1984Q1-2010Q4. These are ratios relative to the RMSFE obtained with the optimal cut-off obtained in the sample 1984Q1-2010Q4. Clearly, since the denominator in this ratio is based on the optimal cut-offs for the sample 1984Q1-2010Q4 all the values in table 5 are directly comparable to those in table 3 and necessarily greater than 1 (exactly equal to 1 when the optimal cut-off period coincides).

Table 4 reveals that the optimal cut-off period varies somehow across samples, but most often within reasonable intervals. Interestingly, it is still true that, for a given sample, the optimal cut-off period generally increases with the forecast horizon. Also, for many variables there is noticeable stability, for each forecast horizon, in the optimal cut-off period across samples (see, e.g., results for the unemployment rate, real output or real PCE).[14] Relevantly, the optimal cut-offs obtained in the sample 1974Q1-1983Q4 are most often not very different from the ones obtained in the other samples. Now, more important than the stability or value of the cut-offs is the forecast accuracy loss implied by sub-optimal choices of those cut-offs. Table 5 reveals that, even if the cut-off period is not fully stable across samples, the differences in forecast accuracy implied by a sub-optimal choice of cut-off period are not very damaging to the LPF. Further, in the cases where the difference is consistently substantial (say, for GDP inflation and the CPI), the fall in forecast accuracy is, broadly speaking, not enough to annul the overall lead of the LPF vis-a-vis the other methods. This is specially evident at long horizons. Even more important is the fact that the conclusions above generally hold if the

[14]Generally, in cases where the difference in the optimal cut-off vis-a-vis the sample 1984Q1-2010Q4 is striking, e.g. the really low cut-offs for $h = 8, 12$ in the sample 1974Q1-1983Q4 for real state and local spending as well as for real federal spending, it turns out that the RMSFE, as a function of the cut-off period, has two local minima: the one reported in table 4 (which is global minima) and another one close to the value found for 1984Q1-2010Q4 and/or close to the value found for adjacent horizons in the same sample.

Table 4

Optimal cut-off period by forecast horizon for each variable and sample period. Estimation sample begins always in 1959Q2.

		Forecast horizon					
Variable	**Sample Period**	1	2	4	6	8	12
Nominal output	1984Q1-2010Q4	8	12	12	12	20	28
	1974Q1-1983Q4	36	36	36	40	40	12
	1974Q1-1990Q4	8	36	36	36	40	12
	1974Q1-2000Q4	8	36	36	36	40	12
Unemployment rate	1984Q1-2010Q4	4	12	12	20	20	20
	1974Q1-1983Q4	4	4	4	20	20	20
	1974Q1-1990Q4	4	4	8	20	20	20
	1974Q1-2000Q4	4	8	8	16	20	20
Industrial production index	1984Q1-2010Q4	4	8	12	4	4	28
	1974Q1-1983Q4	4	8	4	16	16	20
	1974Q1-1990Q4	4	8	4	12	12	20
	1974Q1-2000Q4	4	8	4	4	12	44
3-Month treasury bill rate	1984Q1-2010Q4	8	8	16	16	16	20
	1974Q1-1983Q4	4	4	4	4	20	20
	1974Q1-1990Q4	4	4	4	4	32	32
	1974Q1-2000Q4	4	4	4	4	20	20
Real output	1984Q1-2010Q4	8	8	16	20	20	32
	1974Q1-1983Q4	8	8	8	20	20	20
	1974Q1-1990Q4	8	8	8	16	20	20
	1974Q1-2000Q4	8	8	8	16	20	20
Real Personal Consumption Expenditures	1984Q1-2010Q4	16	16	20	24	36	40
	1974Q1-1983Q4	12	12	12	20	20	20
	1974Q1-1990Q4	12	12	20	20	20	36
	1974Q1-2000Q4	12	12	20	20	20	36
Real private nonresidential fixed investment	1984Q1-2010Q4	8	12	12	12	12	20
	1974Q1-1983Q4	8	8	8	8	20	20
	1974Q1-1990Q4	8	8	8	8	20	20
	1974Q1-2000Q4	8	8	16	4	48	48
Real state & local consumption expenditures & gross investment	1984Q1-2010Q4	20	20	20	20	20	36
	1974Q1-1983Q4	48	48	48	48	8	12
	1974Q1-1990Q4	20	48	12	48	8	12
	1974Q1-2000Q4	20	40	20	40	8	40
GDP deflator	1984Q1-2010Q4	16	28	28	28	28	28
	1974Q1-1983Q4	8	12	20	48	48	48
	1974Q1-1990Q4	8	12	20	40	48	48
	1974Q1-2000Q4	8	12	20	44	48	48
Housing starts	1984Q1-2010Q4	28	28	28	32	32	32
	1974Q1-1983Q4	4	4	16	16	20	20
	1974Q1-1990Q4	4	4	16	16	20	20
	1974Q1-2000Q4	20	4	16	16	20	20
Real private residential fixed investment	1984Q1-2010Q4	8	28	28	28	32	28
	1974Q1-1983Q4	4	16	16	16	20	20
	1974Q1-1990Q4	4	8	16	16	20	20
	1974Q1-2000Q4	4	8	16	16	20	20
Consumer price index	1984Q1-2010Q4	32	32	32	32	32	32
	1974Q1-1983Q4	8	16	16	48	48	48
	1974Q1-1990Q4	8	16	16	40	44	48
	1974Q1-2000Q4	8	16	16	40	44	48
Real federal consumption expenditures & gross investment	1984Q1-2010Q4	48	44	44	44	48	48
	1974Q1-1983Q4	48	48	24	24	8	4
	1974Q1-1990Q4	48	48	44	24	4	48
	1974Q1-2000Q4	48	48	44	48	48	48

Table 5

RMSFE of LPF forecasts with cut-off choice based on different samples relative to RMSFE obtained with the optimal cut-off in the sample 1984Q1-2010Q4. Evaluation period is always 1984Q1-2010Q4 and estimation sample begins always in 1959Q2.

		Forecast horizon					
Variable	**Sample for Cut-off choice:**	1	2	4	6	8	12
Nominal output	1974Q1-1983Q4	1.138	1.078	1.046	1.042	1.037	1.044
	1974Q1-1990Q4	1.000	1.078	1.046	1.039	1.037	1.044
	1974Q1-2000Q4	1.000	1.078	1.046	1.039	1.037	1.044
Unemployment rate	1974Q1-1983Q4	1.000	1.028	1.052	1.000	1.000	1.000
	1974Q1-1990Q4	1.000	1.028	1.048	1.000	1.000	1.000
	1974Q1-2000Q4	1.000	1.003	1.048	1.011	1.000	1.000
Industrial production index	1974Q1-1983Q4	1.000	1.000	1.034	1.029	1.020	1.005
	1974Q1-1990Q4	1.000	1.000	1.034	1.016	1.008	1.005
	1974Q1-2000Q4	1.000	1.000	1.034	1.000	1.008	1.012
3-Month treasury bill rate	1974Q1-1983Q4	1.033	1.105	1.015	1.023	1.001	1.000
	1974Q1-1990Q4	1.033	1.105	1.015	1.023	1.022	1.001
	1974Q1-2000Q4	1.033	1.105	1.015	1.023	1.001	1.000
Real output	1974Q1-1983Q4	1.000	1.000	1.051	1.000	1.000	1.008
	1974Q1-1990Q4	1.000	1.000	1.051	1.001	1.000	1.008
	1974Q1-2000Q4	1.000	1.000	1.051	1.001	1.000	1.008
Real Personal Consumption Expenditures	1974Q1-1983Q4	1.001	1.007	1.041	1.001	1.014	1.030
	1974Q1-1990Q4	1.001	1.007	1.000	1.001	1.014	1.001
	1974Q1-2000Q4	1.001	1.007	1.000	1.001	1.014	1.001
Real private nonresidential fixed investment	1974Q1-1983Q4	1.000	1.006	1.038	1.018	1.002	1.000
	1974Q1-1990Q4	1.000	1.006	1.038	1.018	1.002	1.000
	1974Q1-2000Q4	1.000	1.006	1.032	1.010	1.030	1.011
Real state & local consumption expenditures & gross investment	1974Q1-1983Q4	1.086	1.066	1.044	1.039	1.029	1.033
	1974Q1-1990Q4	1.000	1.066	1.035	1.039	1.029	1.033
	1974Q1-2000Q4	1.000	1.049	1.000	1.023	1.029	1.000
GDP deflator	1974Q1-1983Q4	1.082	1.022	1.011	1.154	1.170	1.159
	1974Q1-1990Q4	1.082	1.022	1.011	1.080	1.170	1.159
	1974Q1-2000Q4	1.082	1.022	1.011	1.117	1.170	1.159
Housing starts	1974Q1-1983Q4	1.080	1.072	1.035	1.041	1.029	1.018
	1974Q1-1990Q4	1.080	1.072	1.035	1.041	1.029	1.018
	1974Q1-2000Q4	1.007	1.072	1.035	1.041	1.029	1.018
Real private residential fixed investment	1974Q1-1983Q4	1.014	1.017	1.069	1.090	1.062	1.040
	1974Q1-1990Q4	1.014	1.047	1.069	1.090	1.062	1.040
	1974Q1-2000Q4	1.014	1.047	1.069	1.090	1.062	1.040
Consumer price index	1974Q1-1983Q4	1.121	1.065	1.066	1.070	1.081	1.095
	1974Q1-1990Q4	1.121	1.065	1.066	1.031	1.059	1.095
	1974Q1-2000Q4	1.121	1.065	1.066	1.031	1.059	1.095
Real federal consumption expenditures & gross investment	1974Q1-1983Q4	1.000	1.002	1.011	1.024	1.043	1.027
	1974Q1-1990Q4	1.000	1.002	1.000	1.024	1.026	1.000
	1974Q1-2000Q4	1.000	1.002	1.000	1.000	1.000	1.000

choice of cut-off period is fully based on data available before the evaluation period, i.e., based on the sample 1974Q1-1983Q4. Still, we must acknowledge that a cut-off based on these samples would imply loosing the lead (or reinforcing the lag) in various instances when $h = 1$ and for various horizons in the cases of real state and local spending, housing starts, real nonresidential investment and the industrial production index.

5 Conclusions

We have shown how simple univariate low-frequency filters can be usefully applied to macroeconomic forecasting. We started with the observation that targeting a smooth version of a time series may be more useful than targeting the sometimes erratic (or unpredictable at high frequencies) original series, specially at long horizons. Conventional forecast models initially fit the variables of interest at every frequency, regardless of the predictability of the series at high frequencies. The optimal degree of smoothness depends on the specific series at hand and on the forecast horizon but we were able to characterize this optimal choice for a relevant group of macroeconomic time series. We plan to explore the theoretical underpinnings of these results in future research. Finally, it is also worth performing a systematic study of all these issues within a multivariate setting, see Valle e Azevedo and Pereira (2008) and Wildi and Sturm (2008) for specific applications.

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Data Appendix

Our data for the SPF predictions comes directly from the Federal Reserve Bank of Philadelphia website and covers the period 1968Q4-2010Q4.[15] We use the June 2011 vintage of all series (against which forecasts are compared) available at the same website. Data is converted to quarterly whenever the series are available at a higher frequency (by averaging the observations within each quarter and to match exactly the target of SPF panelists). Except for unemployment and interest rates, all data is in growth rates. Except for interest rates, all published data is seasonally adjusted, in accordance with the target of SPF's forecasts. Prior to 1992, nominal and real output forecasts refer to nominal GNP. GDP deflator forecasts refer to GNP deflator prior to 1992, to GDP deflator from 1992 through 1995 and to chain-weighted price index for GDP since 1996.

Regarding the panel of predictors, we use the monthly time series used in Stock and Watson (2002a) to estimate common factors, following the transformations suggested there. A few variables

[15] http://www.phil.frb.org/econ/spf/spfpage.html. For a recent discussion about the Phil-SPF see Croushore (2006).

were substituted (by variables conveying similar information) and others dropped due to lack of free public availability. Most series were downloaded from the FRED database (Federal Reserve Bank of St. Louis). This dataset covers the period from 1959 January/Q1 to 2010 December/Q4 2010. The $n = 83$ available time series were realigned to account for release delays.

The following table shows the definition of the forecasted series, Phil-SPF's and FRED's id code and observation range.

Title	RTDSM/FRED id	Phil-SPF id	Transf.(1)	Sample period(2)	Description(3)
Nominal GNP/GDP	NOUTPUT	NGDP	Δln	1959:Q1-2010:Q4	SAAR; Billions of dollars
Real GNP/GDP	ROUTPUT	RGDP	Δln	1959:Q1-2010:Q4	SAAR; Billions of chained 2005 dollars
Real Personal Consumption Expenditures - Total	RCON	RCONSUM	Δln	1959:Q1-2010:Q4	SAAR; Billions of chained 2005 dollars
Price Index for GNP/GDP	P	PGDP	Δln	1959:Q1-2010:Q4	SA; Index 2005=100
Consumer Price Index	CPI	CPI	Δln	1959:M1-2010:M12	SA; Index 1982-84=100
Real Gross Private Domestic Investment - Residential	RINVRESID	RRESINV	Δln	1959:Q1-2010:Q4	SAAR; Billions of chained 2005 dollars
Real Gross Private Domestic Investment - Nonresidential	RINVBF	RNRESIN	Δln	1959:Q1-2010:Q4	SAAR; Billions of chained 2005 dollars
Real Government Consumption and Gross Investment - State and Local	RGLS	RSLGOV	Δln	1959:Q1-2010:Q4	SAAR; Billions of chained 2005 dollars
Real Government Consumption and Gross Investment - Federal	RGF	RFEDGOV	Δln	1959:Q1-2010:Q4	SAAR; Billions of chained 2005 dollars
Housing Starts	HSTARTS	HOUSING	Δln	1959:M1-2010:M12	SAAR; Thousands of units
Industrial Production Index - Total	IPT	INDPROD	Δln	1959M1-2010:M12	SA; Index 2007=100
Unemployment Rate	RUC	UNEMP	Δlev	1959:M1-2010:M12	SA; Percent
3-Month Treasury Bill Rate	TB3MS	TBILL	Δlev	1959:M1-2010:M12	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 presents the characteristics of the predictors used in the multivariate approaches. All predictors were downloaded from the FRED database of the Federal Reserve Board of St. Louis. Monthly predictors are first converted to quarterly data (as 3-months averages) before any necessary transformations to render the series stationary.

Title	**FRED id**	**Transf.**$^{(1)}$	**Sample Period**$^{(2)}$	**Description**$^{(3)}$
Real Gross Domestic Product	GDPC1	Δln	1959:Q1-2010:Q4	SAAR; Billions of chained 2005 dollars
Real Disposable Personal Income	DPIC96	Δln	1959:Q1-2010:Q4	SAAR; Billions of chained 2005 dollars
Real Personal Consumption Expenditures	PCECC96	Δln	1959:Q1-2010:Q4	SAAR; Billions of chained 2005 dollars
Real Personal Consumption Expenditures: Services	PCESVC96	Δln	1959:Q1-2010:Q4	SAAR; Billions of chained 2005 dollars
Real Personal Consumption Expenditures: Durable Goods	PCDGCC96	Δln	1959:Q1-2010:Q4	SAAR; Billions of chained 2005 dollars
Real Personal Consumption Expenditures: Nondurable Goods	PCNDGC96	Δln	1959:Q1-2010:Q4	SAAR; Billions of chained 2005 dollars
Real Private Residential Fixed Investment	PRFIC1	Δln	1959:Q1-2010:Q4	SAAR; Billions of chained 2005 dollars
Real Private Nonresidential Fixed Investment	PNFIC1	Δln	1959:Q1-2010:Q4	SAAR; Billions of chained 2005 dollars
Real State & Local Consumption Expenditures & Gross Investment	SLCEC1	Δln	1959:Q1-2010:Q4	SAAR; Billions of chained 2005 dollars
Real Federal Consumption Expenditures & Gross Investment	FGCEC1	Δln	1959:Q1-2010:Q4	SAAR; Billions of chained 2005 dollars
Consumer Price Index for All Urban Consumers: All Items	CPIAUCSL	Δln	1959:M1-2010:M12	SA; Index 1982-84=100
Consumer Price Index for All Urban Consumers: All Items Less Food	CPIULFSL	Δln	1959:M1-2010:M12	SA; Index 1982-84=100
Consumer Price Index for All Urban Consumers: All Items Less Food & Energy	CPILFESL	Δln	1959:M1-2010:M12	SA; Index 1982-84=100
Consumer Price Index for All Urban Consumers: Apparel	CPIAPPSL	Δln	1959:M1-2010:M12	SA; Index 1982-84=100
Consumer Price Index for All Urban Consumers: Medical Care	CPIMEDSL	Δln	1959:M1-2010:M12	SA; Index 1982-84=100
Consumer Price Index for All Urban Consumers: Transportation	CPITRNSL	Δln	1959:M1-2010:M12	SA; Index 1982-84=100
Gross Domestic Product: Chain-type Price Index	GDPCTPI	Δln	1959:Q1-2010:Q4	SA; Index 2005=100
Personal Consumption Expenditures: Chain-type Price Index	PCEPI	Δln	1959:M1-2010:M12	SA; Index 2005=100
Producer Price Index: All Commodities	PPIACO	Δln	1959:M1-2010:M12	NSA; Index 1982=100
Producer Price Index: Crude Materials for Further Processing	PPICRM	Δln	1959:M1-2010:M12	SA; Index 1982=100
Producer Price Index: Finished Consumer Goods	PPIFCG	Δln	1959:M1-2010:M12	SA; Index 1982=100
Producer Price Index: Finished Goods	PPIFGS	Δln	1959:M1-2010:M12	SA; Index 1982=100
Producer Price Index: Intermediate Materials: Supplies & Components	PPIITM	Δln	1959:M1-2010:M12	SA; Index 1982=100
Spot Oil Price: West Texas Intermediate	OILPRICE	Δln	1959:M1-2010:M12	NA; dollars per Barrel
Industrial Production Index	INDPRO	Δln	1959:M1-2010:M12	SA; Index 2007=100
Industrial Production: Consumer Goods	IPCONGD	Δln	1959:M1-2010:M12	SA; Index 2007=100
Industrial Production: Durable Consumer Goods	IPDCONGD	Δln	1959:M1-2010:M12	SA; Index 2007=100
Industrial Production: Nondurable Consumer Goods	IPNCONGD	Δln	1959:M1-2010:M12	SA; Index 2007=100
Industrial Production: Durable Materials	IPDMAT	Δln	1959:M1-2010:M12	SA; Index 2007=100

(1) lev - original level of the series, Δlev - the first difference of the level of the series, ln - logarithm of the series and Δln - first difference of the logarithm of the series.
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continued

Title	FRED id	Transf.(1)	Sample Period(2)	Description(3)
Industrial Production: Nondurable Materials	IPNMAT	Δln	1959:M1-2010:M12	SA; Index 2007=100
Industrial Production: Business Equipment	IPBUSEQ	Δln	1959:M1-2010:M12	SA; Index 2007=100
Industrial Production: Final Products (Market Group)	IPFINAL	Δln	1959:M1-2010:M12	SA; Index 2007=100
Industrial Production: Materials	IPMAT	Δln	1959:M1-2010:M12	SA; Index 2007=100
ISM Manufacturing: PMI Composite Index	NAPM	lev	1959:M1-2010:M12	SA; Index
ISM Manufacturing: Employment Index	NAPMEI	lev	1959:M1-2010:M12	SA; Index
ISM Manufacturing: Inventories Index	NAPMII	lev	1959:M1-2010:M12	SA; Index
ISM Manufacturing: New Orders Index	NAPMNOI	lev	1959:M1-2010:M12	SA; Index
ISM Manufacturing: Production Index	NAPMPI	lev	1959:M1-2010:M12	SA; Index
ISM Manufacturing: Supplier Deliveries Index	NAPMSDI	lev	1959:M1-2010:M12	SA; Index
Housing Starts: Total: New Privately Owned Housing Units Started	HOUST	ln	1959:M1-2010:M12	SAAR; Thousands of units
Housing Starts in Midwest Census Region	HOUSTMW	ln	1959:M1-2010:M12	SAAR; Thousands of units
Housing Starts in Northeast Census Region	HOUSTNE	ln	1959:M1-2010:M12	SAAR; Thousands of units
Housing Starts in South Census Region	HOUSTS	ln	1959:M1-2010:M12	SAAR; Thousands of units
Housing Starts in West Census Region	HOUSTW	ln	1959:M1-2010:M12	SAAR; Thousands of units
Real Exports of Goods & Services	EXPGSC96	Δln	1959:Q1-2010:Q4	SAAR; Billions of chained 2005 dollars
Real Change in Private Inventories	CBIC1	ln	1959:Q1-2010:Q4	SAAR; Billions of chained 2005 dollars
Civilian Unemployment Rate	UNRATE	lev	1959:M1-2010:M12	SA; Percent
Civilians Unemployed - Less Than 5 Weeks	UEMPLT5	Δln	1959:M1-2010:M12	SA; Thousands of persons
Civilians Unemployed for 5-14 Weeks	UEMP5TO14	Δln	1959:M1-2010:M12	SA; Thousands of persons
Civilians Unemployed for 15-26 Weeks	UEMP15T26	Δln	1959:M1-2010:M12	SA; Thousands of persons
Civilians Unemployed for 27 Weeks and Over	UEMP27OV	Δln	1959:M1-2010:M12	SA; Thousands of persons
Civilians Unemployed - 15 Weeks & Over	UEMP15OV	Δln	1959:M1-2010:M12	SA; Thousands of persons
Average (Mean) Duration of Unemployment	UEMPMEAN	Δln	1959:M1-2010:M12	SA; Weeks
Civilian Employment	CE16OV	Δln	1959:M1-2010:M12	SA; Thousands of persons
All Employees: Manufacturing	MANEMP	Δln	1959:M1-2010:M12	SA; Thousands
All Employees: Nondurable goods	NDMANEMP	Δln	1959:M1-2010:M12	SA; Thousands
All Employees: Service-Providing Industries	SRVPRD	Δln	1959:M1-2010:M12	SA; Thousands
All Employees: Construction	USCONS	Δln	1959:M1-2010:M12	SA; Thousands
All Employees: Financial Activities	USFIRE	Δln	1959:M1-2010:M12	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:M1-2010:M12	SA; Thousands
All Employees: Government	USGOVT	Δln	1959:M1-2010:M12	SA; Thousands
All Employees: Mining and logging	USMINE	Δln	1959:M1-2010:M12	SA; Thousands
All Employees: Total Private Industries	USPRIV	Δln	1959:M1-2010:M12	SA; Thousands
All Employees: Trade, Transportation & Utilities	USTPU	Δln	1959:M1-2010:M12	SA; Thousands
All Employees: Retail Trade	USTRADE	Δln	1959:M1-2010:M12	SA; Thousands
All Employees: Durable goods	DMANEMP	Δln	1959:M1-2010:M12	SA; Thousands
Compensation of Employees: Wages & Salary Accruals	WASCUR	Δln	1959:Q1-2010:Q4	SAAR; Billions of dollars
Average Weekly Hours of Production and Nonsupervisory Employees: Manufacturing	AWHMAN	Δln	1959:M1-2010:M12	SA; Hours
Average Weekly Overtime Hours of Production and Nonsupervisory Employees: Manufacturing	AWOTMAN	Δln	1959:M1-2010:M12	SA; Hours
3-Month Treasury Bill: Secondary Market Rate	TB3MS	Δlev	1959:M1-2010:M12	NA; Percent
6-Month Treasury Bill: Secondary Market Rate	TB6MS	Δlev	1959:M1-2010:M12	NA; Percent
1-Year Treasury Constant Maturity Rate	GS1	Δlev	1959:M1-2010:M12	NA; Percent
10-Year Treasury Constant Maturity Rate	GS10	Δlev	1959:M1-2010:M12	NA; Percent
5-Year Treasury Constant Maturity Rate	GS5	Δlev	1959:M4-2010:M12	NA; Percent
Effective Federal Funds Rate	FEDFUNDS	Δlev	1959:M1-2010:M12	NA; Percent
Moody's Seasoned Aaa Corporate Bond Yield	AAA	Δlev	1959:M1-2010:M12	NA; Percent
Moody's Seasoned Baa Corporate Bond Yield	BAA	Δlev	1959:M1-2010:M12	NA; Percent
Corporate Profits After Tax	CP	Δln	1959:Q1-2010:Q4	SAAR; Billions of dollars
M1 Money Stock	M1SL	Δln	1959:M1-2010:M12	SA; Billions of dollars
M2 Money Stock	M2SL	Δln	1959:M1-2010:M12	SA; Billions of dollars
Board of Governors Monetary Base, Adjusted for Changes in Reserve Requirements	BOGAMBSL	Δln	1959:M1-2010:M12	SA; Billions of dollars
Non-Borrowed Reserves of Depository Institutions	BOGNONBR	Δln	1959:M1-2010:M12	SA; Billions of dollars
Total Nonrevolving Credit Outstanding	NONREVSL	Δln	1959:M1-2010:M12	SA; Billions of dollars

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