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What do professional forecasters actually predict?

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A B S T R A C T

This paper studies what professional forecasters predict. We use spectral analysis and state space modeling to decompose economic time series into trend, business cycle, and irregular components. We examine which components are captured by professional forecasters by regressing their forecasts on the estimated components extracted from both the spectral analysis and the state space model. For both decomposition methods, we find that, in the short run, the Survey of Professional Forecasters can predict almost all of the variation in the time series due to the trend and the business cycle, but that the forecasts contain little or no significant information about the variation in the irregular component.

1. Introduction

Econometric models cannot predict events accurately when the developers of the models have failed to include information about the main drivers of the outcomes. The global financial crisis is one example of the failure of models to account for the actual evolution of the real-world economy (Colander et al., 2009). In addition to econometric models, surveys of forecasters also provide predictions about key economic variables. Although professional forecasters cannot predict one-off events, like natural disasters, they may take interpretations of news and various expert opinions into account more quickly than econometric models when forming a final prediction. Fiscal, political, and weather conditions can all be reasons for experts to arrive at predictions that differ from model-based forecasts. The amount of attention that these surveys receive indicates that they are perceived to contain useful information about the economy (as Ghysels & Wright, 2009, note).

This paper examines what professional forecasters actually are able to predict. Do they only explain movements in economic time series which can also be explained by regular components like a trend or a business cycle, or do they also explain part of the irregular component, which can hardly be predicted by econometric models or non-experts? We address this question by decomposing five key economic variables (GDP, the GDP deflator, unemployment, industrial production and housing starts) of the US economy into three components, then examining whether panelists of the Survey of Professional Forecasters can explain the variation in the time series that is due to the different estimated components.

We decompose the economic variables by applying two methods that are used commonly in the literature for extracting trends and business cycles from time series. First, we apply the Baxter and King (1999) low-pass filter that Baxter (1994) uses for the decomposition of exchange rate series into trend, business cycle, and irregular components. Second, we also decompose the time series into trend, cycle, and irregular components using the state space model that is studied by Harvey (1985). Since the two decompositions rely on different assumptions, we apply both methods and compare the two to assess whether the results are robust. The low-pass filter and the state space model are used to estimate the trend and cycle as precisely as possible, and are not considered as the true data generating process for the observed time series. Next, we regress the forecasts of the professional forecasters on

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the estimated components in both the spectral analysis and the state space model. We deal with the presence of a unit root in the forecasts and the estimated trend by using the framework of Park and Phillips (1989), and account for two-step uncertainty in the standard errors by implementing the procedure of Murphy and Topel (2002).

Our results show that professional forecasters can predict almost all of the variation in the time series due to the trend and business cycle components in the short run, but explain little or nothing of the variation in the irregular component. The small amount of variation in the irregular components that the professional forecasters capture may explain why some businesses and policymakers rely on professional forecasters. The two approaches to decomposing the time series lead to approximately the same results in the forecast regressions. The prediction of the cyclical component worsens for longer forecast horizons. The results look very similar if we replace the professional forecasts by simple time series model forecasts. With respect to root mean squared prediction errors, professional forecasters perform slightly better than the structural time series models that are used commonly for estimating trends and cycles in time series. However, the difference is significant only in a particular sample period. Finally, our results suggest that professional forecasters seem to explain the realized values in the current period, which has already been published, instead of explaining irregular events in the future.

Although forecast performance is a widely debated topic, we are the first, to the best of our knowledge, to assess forecasts from the perspective of 'what' is predicted instead of 'how well' the actual values are predicted. Hyndman and Koehler (2006) state that "despite two decades of papers on measures of forecast error", the recommended measures still have some fundamental problems. Moreover, all of these measures are relative and have to be compared to a benchmark model. If we instead assess whether a significant amount of the variation in the different components of a time series can be explained, no benchmark forecast is needed. Leitch and Ernesttanner (1995) show that conventional forecast evaluation criteria have little to do with the profitability of forecasts, which explains why firms spends millions of dollars on purchasing professional forecasts. These firms may believe that experts have information about irregular movements in the future which cannot be predicted by econometric models.

The performances of professional forecasts have been the subject of a number of studies. Gil-Alana, Moreno, and Pérez de Gracia (2012), Mehra (2002), and Thomas (1999) show that forecast surveys outperform benchmark models for forecasting inflation. These papers focus on the strength of expert forecasts relative to other forecasting methods. In a comprehensive study, Ang, Bekaert, and Wei (2007) also show that professional forecasters outperform other forecasting methods for predicting inflation by means of relative measures and combinations of forecast methods. However, instead of focusing on the relative strength of expert forecasts, we question what professional forecasters actually predict. Moreover, where other studies focus only on forecasting inflation, we also consider other key variables of the US economy. Franses, Kranendonk, and Lanser (2011) examine forecasts of various Dutch macroeconomic variables and conclude that expert forecasts are more accurate than model-based forecasts. Other papers show professionals' forecasts to add limited value. Franses and Legerstee (2010) show that, in general, experts are worse than econometric models for forecasting sales at the stock keeping unit level. Isiklar, Lahiri, and Loungani (2006) find that the professional forecasts of Consensus Economics do not include all available new information. Coibion and Gorodnichenko (2012, 2015) find persistence in the forecast errors for the GDP deflator of the Survey of Professional Forecasters. In a comparison between the forecasts of professional forecasters and their long-run expectations, Clements (2015) finds little evidence that the forecasts of the Survey of Professional Forecasters are any more accurate than forecasting the trend. Billio, Casarin, Ravazzolo, and Van Dijk (2013) show that the performance trade-off between a white noise model and professional forecasts for predicting returns varies over time. There is also a body of literature that uses professional forecasts to improve models. For instance, Kozicki and Tinsley (2012) incorporate survey data in a model for inflation in order to have timely information on structural change, Mertens (2016) estimates trend inflation with the help of survey expectations, and Altug and Çakmaklı (2016) claim a superior predictive power of models of inflation when survey expectations are incorporated.

The outline of this paper is as follows. Section 2 explains the decomposition methods of the economic time series and the forecast regressions of the professional forecasts on the estimated components. Section 3 describes the economic time series and the corresponding forecasts from the Survey of Professional Forecasters, to which we apply the methods. Section 4 discusses the results obtained from the time series decompositions and the forecast regressions. Section 5 provides comparisons between professional and model-based forecasts in order to provide further insight into the results. We conclude with a discussion in Section 6.

2. Methods

We examine what professional forecasters actually forecast by decomposing the historical values for the predicted time series into three components: trend, business cycle, and an irregular component. Since most macroeconomic surveys provide seasonally adjusted data, we consider seasonally adjusted time series, and hence do not model the seasonal component. However, we argue that our methodology can be extended easily to seasonally unadjusted data. There are two common methods in the literature for decomposing time series: filters in the frequency domain and state space modeling in the time domain. Since the two methods rely on different assumptions (Harvey & Trimbur, 2003), we apply both methods and assess whether the results match.

Section 2.1 discusses the filtering of different components from the time series in a spectral analysis. Section 2.2 deals with the trend-cycle decomposition in a state space framework. Finally, Section 2.3 assesses the forecast regression, where we regress the professional forecasts on both the estimated components in the spectral analysis and the estimated components in the state space framework. The estimated coefficients in these forecast regressions indicate which components can be explained by the professional forecasters.

2.1. Spectral analysis

We consider the model

$$y_t = \mu_t + c_t + \varepsilon_t, \tag{1}$$

where y_t is the observed time series and μ_t represents the trend, c_t the business cycle, and ε_t the irregular component. In other words, we have a slow-moving component, an intermediate component, and a high-frequency component. We isolate these different frequency bands using the low-pass filter derived by Baxter and King (1999). They obtain the component time series by applying moving averages to the observed time series. The time series in a specific frequency band can be isolated by choosing the appropriate weights in the moving average.

The filter produces a new time series x_t by applying a symmetric moving average to the filtered time series y_t:

$$x_t = \sum_{k=-K}^{K} a_k y_{t-k}, \tag{2}$$

with the weights $a_k = a_{-k}$ specified as

$$a_k = b_k + \theta, \tag{3}$$

$$b_k = \begin{cases} \omega/\pi & \text{if } k = 0 \\ \sin(k\omega)/(k\omega) & \text{if } k = 1, \ldots, K, \end{cases} \tag{4}$$

where

$$\theta = \left(1 - \sum_{k=-K}^{K} b_k\right) / (2K + 1) \tag{5}$$

is the normalizing constant which ensures that the low-pass filter places a unit weight at the zero frequency. We denote the low-pass filter by $LP_K(p)$, where K is the lag parameter for which Baxter and King (1999) assessed $K = 12$ as appropriate for quarterly data. This means that we use twelve leads and lags of the data to construct the filter, so three years of observations are lost at the beginning of the sample period and three at the end. The periodicity p of cycles is a function of the frequency ω: $p = 2\pi/\omega$. We follow Baxter and King (1999) in defining the business cycle as cyclical components of at least six quarters and fewer than 32 quarters in duration, and assign all components of lower frequencies to the trend and higher frequencies to the irregular component. Thus, the filtered trend equals $LP_{12}(32)$ and the filtered business cycle is $LP_{12}(6) - LP_{12}(32)$. The filtered irregular component equals the original time series y_t minus the filtered trend and the filtered business cycle component. Note that the low-pass filter "filters" two-sided estimates for the components, which can also be referred to as smoothed estimates of the time series components. It is possible to apply the low-pass filter to seasonally unadjusted data by adding an additional frequency band to the band-pass filter.

In addition to the Baxter and King filter, there are also other filtering methods in the frequency domain which can be used for extracting the trend and business cycle components from a time series. For example, Christiano and Fitzgerald (2003) and Pollock (2000) also propose frequency filters that are suitable for decomposing time series into three components. In our application, we will show that these filters provide results similar to those of the Baxter and King filter.

2.2. State space model

Although the Baxter and King filter is a simple and effective methodology for extracting trends and cycles from time series, it does not allow us to draw any statistical inference on the components. Therefore, we also estimate the components in a model-based approach, in which we obtain confidence intervals for the estimated component series. Moreover, we can estimate the periodicity of the cycle within the model instead of choosing the frequency bands arbitrarily. However, it must be feasible to estimate the model parameters, and we also have to make assumptions on the functional form of the model in the time domain.

A well-known model-based approach in time series decomposition is the state space framework based on the basic structural time series model of Harvey (1990). After including a cyclical component that represents the business cycle, we consider the following model:

$$y_t = \mu_t + c_t + \varepsilon_t, \qquad \varepsilon_t \sim N(0, \sigma_\varepsilon^2), \tag{6}$$

where y_t is the observed time series and μ_t represents the trend, c_t the business cycle, and ε_t the irregular component with variance σ_ε^2. The trend component is specified by the local linear trend model

$$\mu_{t+1} = \mu_t + \nu_t + \xi_t, \qquad \xi_t \sim N(0, \sigma_\xi^2), \tag{7}$$

$$\nu_{t+1} = \nu_t + \zeta_t, \qquad \zeta_t \sim N(0, \sigma_\zeta^2), \tag{8}$$

where ν_t represents the slope of the trend, and σ_ξ^2 and σ_ζ^2 are the variances of the shocks. We opt for a smooth stochastic trend specification as, for example, in Durbin and Koopman (2012), by restricting σ_ξ^2 to zero. The business cycle component is represented by the following relationships:

$$c_{t+1} = \rho c_t \cos\lambda + \rho c_t^* \sin\lambda + \kappa_t, \qquad \kappa_t \sim N(0, \sigma_\kappa^2), \tag{9}$$

$$c_{t+1}^* = -\rho c_t \sin\lambda + \rho c_t^* \cos\lambda + \kappa_t^*, \quad \kappa_t^* \sim N(0, \sigma_\kappa^2), \tag{10}$$

where the unknown coefficients ρ, λ, and σ_κ^2 represent the damping factor, the cyclical frequency, and the cycle error term variance, respectively. The period of the cycle equals $2\pi/\lambda$, and we impose the restrictions $0 < \rho < 1$ and $0 < \lambda < \pi$. For seasonally unadjusted data, we can add a cycle with a seasonal frequency to the state space model, in order to obtain an extra component that captures the seasonal variation.

We estimate the unknown parameters $(\sigma_\varepsilon^2, \sigma_\xi^2, \sigma_\zeta^2, \sigma_\kappa^2, \rho, \lambda)$ in a state space framework:

$$y_t = Z\alpha_t + \varepsilon_t, \qquad \varepsilon_t \sim N(0, \sigma_\varepsilon^2), \tag{11}$$

$$\alpha_{t+1} = T\alpha_t + \eta_t, \qquad \eta_t \sim N(0, Q), \tag{12}$$

where the observation equation relates the observation y_t to the unobserved state vector α_t, which contains the trend and the cycle. This vector is modeled in the state equation. We use Kalman filtering and smoothing to obtain maximum likelihood parameter estimates and estimates for the state vector components (see e.g. Durbin & Koopman, 2012).

The objective of the estimation routine is to minimize the observation noise ε_t relative to the trend and the cycle. Here we are however also interested in the irregular component. Then, instead of allocating all of the variance in the time series to the trend and cycle components, the observation noise has to capture the irregular movement. We prevent the variance of the observation noise σ_ε^2 from going to zero by fixing it to the value of the variance of the estimated irregular component in the low-pass filter.[1] As we show in Section 4.2, our results are robust with respect to alternative values of the variance of the observation noise.

2.3. Forecast regression

Both the spectral analysis and the state space model yield decompositions of the actual values in the historical time series. From here, we investigate how the professional forecasts are related to the components of the historical time series using the regression equation

$$f_{t+h|t} = \beta_0 + \beta_1 \hat{\mu}_{t+h|T} + \beta_2 \hat{c}_{t+h|T} + \beta_3 \hat{\varepsilon}_{t+h|T} + v_{t+h}, \quad (13)$$

where $f_{t+h|t}$ is the professional forecast for h periods ahead conditional on the information known at time t. $\hat{\mu}_{t+h|T}$ represents the estimated trend, $\hat{c}_{t+h|T}$ the estimated business cycle, and $\hat{\varepsilon}_{t+h|T}$ the irregular component. We consider the irregular component, which is constructed by removing the estimated trend and cycle from the observed time series, as an estimate of the irregular variation in the observed time series. The components are estimated using the series y_t for $t = 1, \ldots, T$, where each y_t contains the value observed just before sending out the survey in time period $t + h$. When the professional forecasters predict the actual values perfectly, we have $\hat{\beta} = (\hat{\beta}_0, \hat{\beta}_1, \hat{\beta}_2, \hat{\beta}_3) = (0, 1, 1, 1)$, as the estimated components add up to the actual values. The coefficient β_0 accounts for a potential forecast bias in the case where the coefficients of the estimated components equal one.

It is good to emphasize that we do not consider the models in Eqs. (1) and (6) as the true data generating process for the observed time series. The purpose of these models is to estimate the trend and cycle as precisely as possible. The irregular component is what is left over in the actual series after reasonable estimates of the trend and cycle have been removed. The structural time series model in Eq. (6) imposes that the trend and cycle components be independent. As the trend/cycle estimates follow from filters, the estimated irregular component may be serially correlated as well; however, the persistence in our estimated irregular components is very low. We want to investigate whether professional forecasters can possibly predict some of the variation in the irregular component due to their expert information, despite the assumed absence of persistence in this component.

Since many economic time series exhibit a trending behavior, we expect a stochastic trend in the series of professional forecasts. We model a unit root explicitly in the local linear trend model in the state space framework. Unless professional forecasters have done a very poor job, there is always a long-run relationship between the stochastic trend of the economic time series and the predicted values of this variable. Thus, we expect the forecasts and the estimated trend to be cointegrated. We examine this conjecture in our empirical analysis by testing for cointegration between the professional forecasts and the estimated trend with the Engle and Granger (1987) residual-based cointegration test.

In the case of cointegration, Eq. (13) provides a regression with cointegrated variables f and $\hat{\mu}$ together with the $I(0)$ variables $\hat{c}$ and $\hat{\varepsilon}$. In this situation, Park and Phillips (1989) show that the parameters can be estimated consistently using ordinary least squares. They also provide asymptotically chi-squared distributed Wald test statistics for inference on the estimated parameters (Park & Phillips, 1989, p. 108). We test whether the estimated parameters are individually equal to the values in a perfect forecast. Moreover, we test the null hypothesis of perfectly predicted values; that is, $\beta = (0, 1, 1, 1)$.

The standard errors of the estimated coefficients in Eq. (13) do not account for the uncertainty in the regressors. Due to the fact that the regressors are estimates, we may encounter heteroskedasticity in the residuals; thus, we opt for White standard errors when the components are estimated in the spectral analysis (White, 1980). One of the benefits of the state space model is that it allows us to obtain estimates of the uncertainty in the model parameters. We can exploit the estimated parameter uncertainty in the state space framework by implementing the Murphy and Topel (2002) procedure for computing two-step standard errors. Adjusting the standard covariance matrix of the forecast regression parameters using the state space model parameter covariance matrix results in asymptotically correct standard errors.

It might be appealing to estimate the historical time series components using Eqs. (6)–(10) and the forecast regression coefficients in Eq. (13) simultaneously by including the forecast regression in the state space framework. This allows us to estimate standard errors for the estimated forecast regression coefficients directly, without the concern that we are ignoring the uncertainty in the estimated components. However, this approach allows the forecasts to influence the estimates of the components of the historical time series, which leads to incorrect inference. Thus, we do not consider this simultaneous set-up.

Finally, we want to stress that we use the regression in Eq. (13) only to infer the correlations between the components of the historical time series and the predictions. We do not assume that the forecasters really use the estimated components to arrive at their predictions, or make any other assumption about the generating process of the predictions. Hence, we do not intend to make causality statements.

[1] Stock and Watson (1998) develop estimators and confidence intervals for the parameters in a state space model, where the maximum likelihood estimator of the variance of the stochastic trend has a large point mass at zero. Our situation is different, as we restrict the variance of the observation noise.

Table 1
Timing of the Survey of Professional Forecasters, 1990:Q3 to present.

Survey	Questionnaires sent	Last quarter in panelists' information sets	Deadline for submissions	Results released
Q1	End of January	Q4	Middle of February	Late February
Q2	End of April	Q1	Middle of May	Late May
Q3	End of July	Q2	Middle of August	Late August
Q4	End of October	Q3	Middle of November	Late November

Notes: The first three columns of the table provide the date on which the survey for the current quarter is sent to the panelists and the last quarter of the series of actual historical values that is in the panelists' information sets at this moment. The last two columns indicate when the forecasts for the current quarter must be submitted and when the results of these forecasts are released.

Table 2
Description of the variables.

Variable	Description
NGDP	Annual rate nominal GDP in billion dollars. Prior to 1992, nominal GNP.
PGDP	GDP deflator with varying base years. Prior to 1996, GDP implicit deflator; prior to 1992, GNP deflator.
UNEMP	Unemployment rate in percentage points.
INDPROD	Index of industrial production with varying base years.
HOUSING	Annual rate housing starts, in millions.

Note: All variables are seasonally adjusted.

3. Data

We apply the methods of Section 2 to the well-documented and open database of the Survey of Professional Forecasters. We focus on key variables of the US economy that are available over a long period, namely real-time data of the nominal GDP, the GDP deflator, unemployment, the industrial production index, and housing starts. The forecasts from the Survey of Professional Forecasters are provided by the Federal Reserve Bank of Philadelphia.

We determine the information sets of the forecasters at the moment of providing their forecasts by considering the timing of the survey. The quarterly survey, which was conducted previously by the American Statistical Association and the National Bureau of Economic Research, began in the last quarter of 1968 and was taken over by the Philadelphia Fed in the second quarter of 1990. We collect data up to the second quarter of 2014. Table 1 shows all relevant information concerning the timing of the survey since it has been being conducted by the Philadelphia Fed. There is still some uncertainty about the timing before mid-1990, but the Philadelphia Fed assumes that it is similar to the timing afterwards. Based on this information, we assume that all panelists in the survey are informed about the actual values of the predicted variables up to and including the previous quarter. We use the same information set for constructing the model-based forecasts. Although the exact day of the month on which forecasters have to submit their predictions has changed over time, our results in Section 4.2 turn out to be robust to the differences in timing and to the takeover of the survey by the Philadelphia Fed.

Since the individual forecasters in the survey have limited histories of responses and forecasters may switch identification numbers, we mainly use time series of mean forecasts for the level of economic variables for which the data set includes observations over the whole survey period. The forecasts of the survey panelists are averaged over each time period. In addition to the forecasts, the database of the Survey of Professional Forecasters also provides the real-time quarterly historical values that correspond to the series being predicted. These historical values are included in the information sets of the panelists before they receive the survey for the next quarter. Thus, the Real-Time Data Set for Macroeconomists (Croushore & Stark, 2001) could contain different values if there is a new release of the data after the survey has been sent but before the deadline for returning it. We assess the predictive performance against the time series decompositions of the real-time historical values provided by the survey.

Table 2 lists the series, which are all seasonally adjusted. The unemployment rate, the index of industrial production, and housing starts are averaged over the underlying monthly levels. The base year changed several times over the sample period considered for the GDP deflator and the index of industrial production. We rescale the time series to a base year of 1958 in the case of the GDP deflator and 1957–1959 in the case of the index of industrial production. All base year changes, temporal aggregation, and a detailed explanation of the Survey of Professional Forecasters can be found in the documentation of the Federal Reserve Bank of Philadelphia.[2]

This paper considers the logarithm of all historical time series and forecasts multiplied by one hundred. Fig. 1 shows these key variables of the US economy. The solid line corresponds to the historical time series and the dashed dotted line to the difference between the historical values and the predictions by the Survey of Professional Forecasters. We recognize an upward trend in the nominal GDP, the GDP deflator, and the industrial production index. The latter two also show some cyclical movements. We cannot identify a trend directly for unemployment and housing, but we see clear cyclical patterns in these series.

2 http://www.philadelphiafed.org/research-and-data/real-time-center/survey-of-professional-forecasters/spf-documentation.pdf.

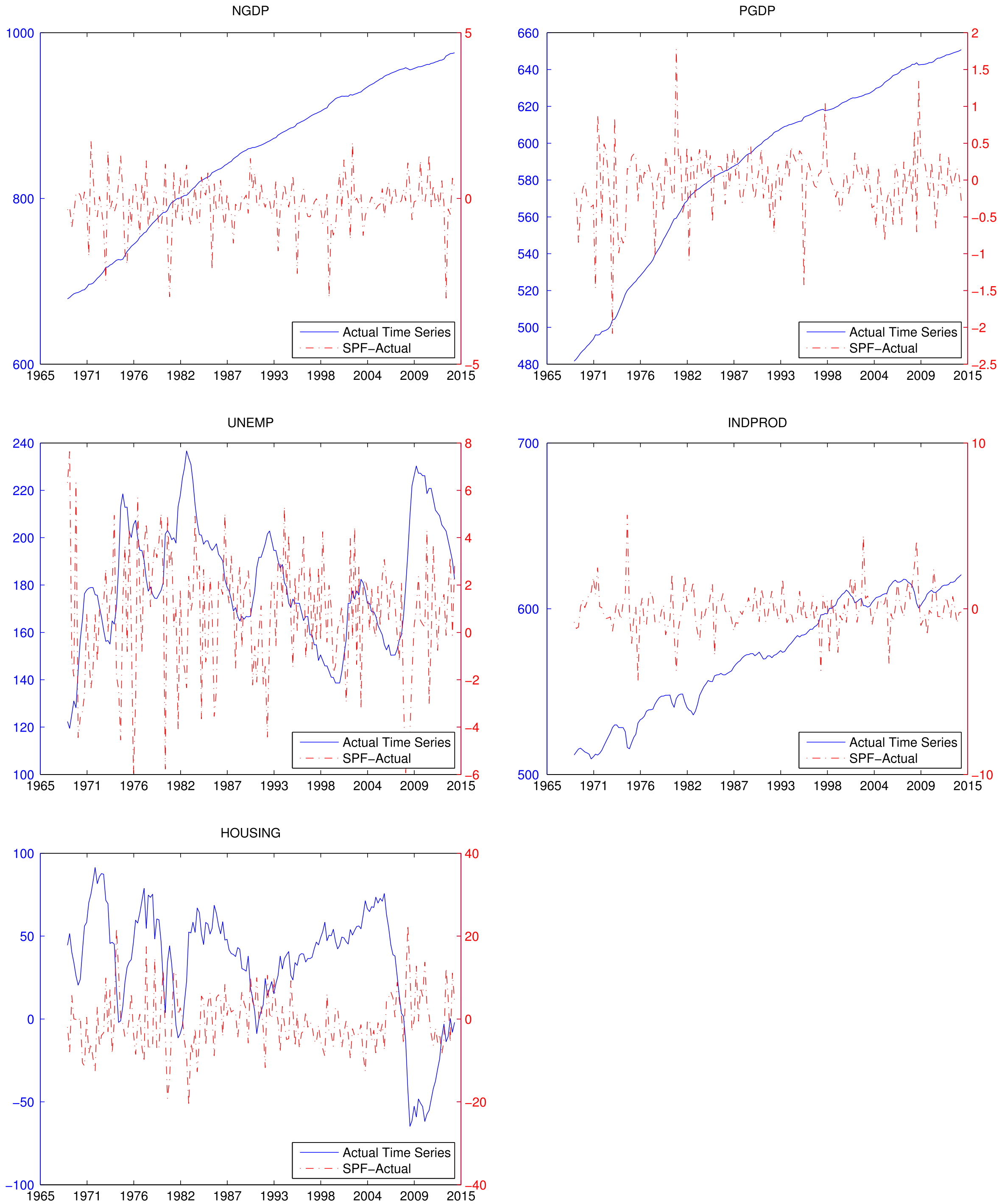

Fig. 1. Historical time series and the survey of professional forecasters. Note: The figure shows historical time series (blue solid line, left axis) graphs, together with the differences between the predictions of the Survey of Professional Forecasters and the actual values (red dashed dotted line, right axis). The panels show the nominal GDP, GDP deflator, unemployment, industrial production index, and housing starts, respectively. The time series are log transformed and multiplied by one hundred.

Table 3 shows the forecast bias for each variable, computed as the average of the difference between the predictions of the Survey of Professional Forecasters and the real-time historical values over different forecast horizons. A positive bias means that the professional forecasters overestimate the actual values on average. The bias is

Table 3
Forecast bias estimates.

Horizon	1	2	3	4	5
NGDP	−0.165	−0.277	−0.324	−0.332	−0.170
	(0.750)	(1.252)	(1.709)	(2.144)	(2.590)
PGDP	−0.012	−0.025	−0.024	−0.025	0.276
	(0.446)	(0.710)	(0.997)	(1.327)	(1.241)
UNEMP	0.799	1.112	0.787	0.111	−0.110
	(2.438)	(5.587)	(8.438)	(11.434)	(13.917)
INDPROD	−0.039	0.122	0.369	0.704	1.031
	(1.284)	(2.425)	(3.493)	(4.406)	(5.080)
HOUSING	−0.391	1.059	3.141	5.262	6.628
	(7.085)	(12.192)	(16.147)	(19.948)	(23.053)

Notes: The table shows the forecast bias, with the standard deviation in parentheses, for each variable over different horizons. The bias is computed as the average of the difference between the predictions of the Survey of Professional Forecasters and the actual historical values. A positive bias means that the forecasters overestimate the actual values on average. Due to missing values, the estimation sample starts at 1974Q4 for $h = 5$.

Table 4
State space model parameter estimates.

	Estimate (std. error)					Implied cycle
	σ_ε	σ_ζ	σ_κ	λ	ρ	
NGDP	0.489	0.142	0.577	0.330	0.910	19
		(0.055)	(0.091)	(0.083)	(0.034)	
PGDP	0.241	0.131	0.218	0.314	0.954	20
		(0.030)	(0.043)	(0.035)	(0.020)	
UNEMP	2.152	0.360	3.791	0.218	0.978	29
		(0.194)	(0.298)	(0.019)	(0.013)	
INDPROD	0.908	0.070	1.454	0.250	0.948	25
		(0.037)	(0.116)	(0.029)	(0.018)	
HOUSING	5.241	0.309	6.721	0.188	0.965	33
		(0.181)	(0.688)	(0.028)	(0.016)	

Notes: The table shows the parameter estimates in the state space model, where the variance of the observation noise σ_ε^2 is fixed to the variance of the irregular component estimated by the low-pass filter. σ_ε represents the standard deviation of the observation noise, σ_ζ the second order trend error term standard deviation, σ_κ the cycle error term standard deviation, λ the cyclical frequency, and ρ the damping factor. The standard errors of the estimates are reported in parentheses. The last column presents the period of the cycle (in quarters), as implied by the λ estimate.

almost always negative but small compared to the standard deviation for the NGPD and PGDP series, but generally positive for the other series.

4. Results

This section discusses the results of our analysis of the predictions of the Survey of Professional Forecasters. First, we consider the decomposition of the actual time series based on both the frequency and time domain analyses. Second, we examine the relationship between the professional forecasts and the estimated components. We first consider one-step-ahead predictions based on the mean of the professional forecasts, then repeat the analysis based on individual forecasts. We end this section by considering multiple-step-ahead forecasts.

4.1. Time series decomposition

Fig. 2 shows the nominal GDP decomposed into a trend, a cycle, and an irregular component by the low-pass filters and the state space model. The two time series follow roughly the same pattern for all components. The fact that the two methods, which rely on different assumptions, result in approximately the same decomposition indicates that the decompositions estimated are reliable. We conclude the same for the other time series, namely the GDP deflator, unemployment, the industrial production index, and housing starts, for which Figs. A.1–A.4 are provided in Appendix A.

Table 4 shows the state space model parameter estimates. Almost all of the parameter estimates are significant. The estimated period of the cycle in the GDP is 19 quarters, which lies within the business cycle period interval defined by Baxter and King. This is also the case for all other variables except for housing starts (33 quarters).

4.2. Forecast regression

As was discussed in Section 2.3, correct inference of the forecast regression parameters in Eq. (13) requires the forecasts to be cointegrated with the estimated trend. Table 5 shows the Engle-Granger cointegration test results on both the estimated trend in the spectral analysis and the estimated trend in the state space model for the one-step-ahead forecasts. The null hypothesis of no cointegration is rejected at the 5% significance level in all cases, except for the trend in the GDP deflator that results from the spectral

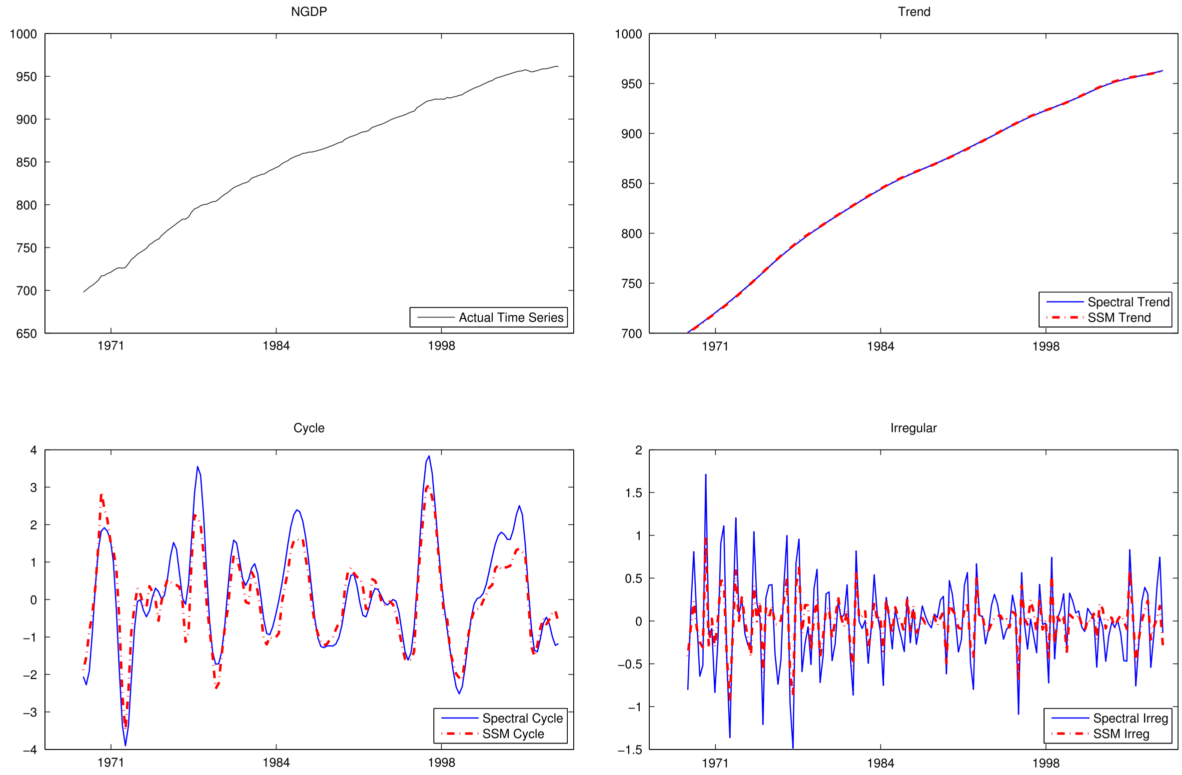

Fig. 2. Decomposition of nominal GDP. Note: The figure shows the nominal GDP decomposed into a trend, a cycle, and an irregular component by the low-pass filters and the state space model. The first panel shows one hundred times the logarithm of the actual values in the historical time series, while the other panels show the components estimated in the low-pass filters as a blue solid line and the components estimated in the state space model as a red dash-dotted line.

Table 5
Cointegration tests of the forecast and trend time series.

	Spectral analysis			State space model		
	τ-stat.	Lags	p-value	τ-stat.	Lags	p-value
NGDP	−5.806	1	0.000	−6.136	1	0.000
PGDP	−2.973	0	0.123	−3.941	0	0.011
UNEMP	−5.538	1	0.000	−4.397	1	0.003
INDPROD	−5.978	1	0.000	−4.814	1	0.001
HOUSING	−3.977	2	0.010	−3.791	1	0.017

This table shows the Engle-Granger residual-based cointegration test of the null hypothesis of no cointegration against the alternative of cointegration. The professional one-step-ahead forecast is the dependent variable and an intercept is included. MacKinnon (1996) p-values are reported and the lag length is specified as the number of lagged differences in the test equation determined by the Schwarz criterion. The first four columns show the results based on the estimated trend in the spectral analysis and the last three columns the results based on the estimated trend in the state space model.

analysis. Hence, we have to be more careful in interpreting the results of the forecast regression for this variable. For the other four variables, we can use the Park and Phillips (1989) test statistics straightforwardly.

We include the estimated components in the forecast regression in Eq. (13) with $h = 1$, in order to examine how the professional one-step-ahead forecasts are related to the different components. Table 6 shows the results based on the estimated components in the spectral analysis and Table 7 shows the results based on the state space model. Due to the lag parameter in the spectral analysis, the filtered series start twelve quarters after the beginning of the sample period and end twelve quarters before the end of the sample period. To make the results comparable, we also exclude these observations from the series estimated in the state space framework, which results in a sample period that goes from the last quarter of 1971 to the second quarter of 2011. Table B.1 in Appendix B reports the results of the spectral analysis based on the Christiano-Fitzgerald and Butterworth filters. Since the outcomes are very similar, we discuss here only the results based on the Baxter and King decomposition.

Tables 6 and 7 show the estimated coefficients for each component, along with the standard errors (in parentheses) and the Wald test statistic on the null hypothesis that the coefficient is equal to the weight expected in a perfect forecast. That is, the intercept is tested against zero and the components against one. These Wald test statistics are asymptotically chi-squared distributed with a critical value of 3.842 at the 5% significance level. Asterisks indicate whether a coefficient differs significantly from the value that would be expected in a perfect forecast. The first five columns of each table show the forecast regression for each variable with an intercept, while the last three columns show the results without an intercept ($\beta_0 = 0$).

The first five columns of Table 6 show that the trend and cycle components receive weights of close to one. Although some of these estimates differ significantly from one due

Table 6
Forecast regressions ($h = 1$) based on spectral analysis.

	Estimate (std. error)				Estimate (std. error)		
	Intercept	Trend	Cycle	Irreg.	Trend	Cycle	Irreg.
	−1.178	1.001	0.954	0.249*	1.000*	0.959	0.248*
NGDP	(0.620)	(0.001)	(0.037)	(0.149)	(0.000)	(0.038)	(0.154)
	3.613	2.752	1.505	25.494	10.051	1.150	23.802
	−0.197	1.000	0.990	−0.132*	1.000	0.992	−0.133*
PGDP	(0.505)	(0.001)	(0.037)	(0.173)	(0.000)	(0.039)	(0.174)
	0.153	0.120	0.080	42.95	0.839	0.045	42.302
	1.318	0.997	0.949*	0.581*	1.004*	0.945*	0.587*
UNEMP	(1.960)	(0.011)	(0.016)	(0.104)	(0.001)	(0.015)	(0.102)
	0.452	0.067	9.966	16.208	18.975	13.982	16.418
	−3.491	1.006	0.938*	0.441*	1.000	0.939*	0.440*
INDPROD	(1.936)	(0.003)	(0.030)	(0.168)	(0.000)	(0.030)	(0.166)
	3.251	3.194	4.386	11.122	0.102	4.246	11.401
	2.555*	0.919*	0.888*	0.239*	0.973*	0.847*	0.252*
HOUSING	(0.880)	(0.022)	(0.038)	(0.119)	(0.010)	(0.036)	(0.119)
	8.423	13.960	8.832	40.781	6.847	18.427	39.817

Notes: The table shows the parameter estimates in the forecast regression in Eq. (13) of the professional forecasts on the low-pass filter decomposition, with and without an intercept. White standard errors are reported in parentheses, together with Wald test statistics on the null hypothesis that the coefficient is equal to the weight expected in a perfect forecast.

* Indicates that the coefficient differs significantly from the weight expected in a perfect forecast at the 5% significance level.

to the small standard errors, it is clear that the professional forecasters can predict most of the variation that is caused by a trend and a business cycle. However, the parameter estimates that correspond to the irregular component differ significantly from one and have large standard errors. Moreover, some of the weights on the irregular components do differ significantly from zero, which means that the professional forecasters still seem to capture a bit of the irregular movement in the time series.

When the weights of the estimated components are equal to one, the estimated intercept accounts for a potential bias in the level of the forecasts. Because most variables are underestimated by the professional forecasters on average, we estimate a negative intercept in most cases. The estimated weights of the components do not change much when we do not include an intercept: the estimated weights for the trend and the cycle are close to one and the weights on the irregular component are similar to before (last three columns of Table 6). Moreover, unreported results show that setting the coefficients of the trend and cycle components to one makes hardly any difference to the results with respect to the estimated weights of the irregular components.

Table 7 shows the results based on the estimated components in the state space model, and finds almost the same results. Again, the estimated weights for the trend and cycle components are close to one. However, in the case of the state space analysis it is remarkable that all of the estimated weights for the irregular components are negative, and about half are even significantly different from zero. Again, the Wald test on the null hypothesis that the professional forecasters predict perfectly is rejected for all variables, with p-values equal to 0.000. Some of the estimated weights for the trend and cycle components differ significantly from one, for example those for the GDP deflator and housing starts.

One could argue that the results in Tables 6 and 7 may have been different before the Philadelphia Fed took over the survey from the period thereafter. However, a dummy for the period after the take-over is almost never significant at the 5% level and does not change the estimated coefficients of the components significantly; thus, it is omitted from the reported forecast regressions. We also account for the varying calender dates for the survey deadline, as well for the release dates of the survey results. These dates are documented from the moment that the Fed took over the survey. For this sample period, we include a dummy indicating whether the number of days between the last release and the next deadline is above or below the median. Again, we do not find significant estimates, and hence omit this dummy. We make sure that our results are robust to definition changes by also performing the analysis in Table 6 on the first differences of the series, where the first differences are constructed using the vintages in the real-time dataset. Appendix C shows the results. We find that the weights of the business cycle are not all as close to one as was the case for the level data, but the weights of the irregular components are again significantly different from one.

While we reported White standard errors and the corresponding Wald statistics in the case of the components estimated in the spectral analysis in Table 6, Table 7 reports ordinary standard errors and Wald statistics. These standard errors do not take into account the fact that the regressors are estimates. Since we obtain an estimated covariance matrix of the estimated parameters in the state space framework, we can adjust the ordinary standard errors for the uncertainty in the regressors. Table 8 shows the effect of the uncertainty in the estimated components of the state space model on the results of the forecast regression by reporting two-step standard errors and the corresponding Wald statistics.

The second column of Table 8 shows that the standard errors of the intercepts are now even larger. However, the forecast biases for the nominal GDP, the industrial production index, and housing starts are still significantly

Table 7
Forecast regressions ($h = 1$) based on a state space model.

	Estimate (std. error)				Estimate (std. error)		
	Intercept	Trend	Cycle	Irreg.	Trend	Cycle	Irreg.
	−1.242*	1.001	1.063	−0.596*	1.000*	1.061	−0.587*
NGDP	(0.553)	(0.001)	(0.044)	(0.194)	(0.000)	(0.045)	(0.196)
	5.049	3.794	2.009	67.910	10.242	1.861	65.503
	−0.316	1.001	1.096*	−0.804*	1.000	1.100*	−0.805*
PGDP	(0.387)	(0.001)	(0.042)	(0.171)	(0.000)	(0.042)	(0.171)
	0.666	0.627	5.242	111.429	0.100	5.757	111.773
	0.015	1.004	0.980	−0.024*	1.004*	0.980	−0.024*
UNEMP	(2.082)	(0.011)	(0.011)	(0.190)	(0.001)	(0.011)	(0.189)
	0.000	0.145	3.073	29.212	21.326	3.139	29.413
	−3.708*	1.006*	0.989	−0.443*	0.999	0.988	−0.436*
INDPROD	(1.689)	(0.003)	(0.020)	(0.229)	(0.000)	(0.021)	(0.231)
	4.821	4.724	0.300	39.817	0.126	0.362	38.506
	4.520*	0.866*	0.971	−0.381*	0.975*	0.939*	−0.340*
HOUSING	(1.240)	(0.032)	(0.020)	(0.136)	(0.011)	(0.018)	(0.141)
	13.292	17.822	2.086	103.030	5.243	10.927	90.524

Notes: The table shows the parameter estimates in the forecast regression in Eq. (13) of the professional forecasts on the state space model decomposition, with and without an intercept. Standard errors are reported in parentheses, together with Wald test statistics on the null hypothesis that the coefficient is equal to the weight expected in a perfect forecast.

* Indicates that the coefficient differs significantly from the weight expected in a perfect forecast at the 5% significance level.

Table 8
Forecast regressions ($h = 1$) with two-step standard errors.

	Estimate (std. error)				Estimate (std. error)		
	Intercept	Trend	Cycle	Irreg.	Trend	Cycle	Irreg.
	−1.242*	1.001	1.063	−0.596*	1.000*	1.061	−0.587*
NGDP	(0.553)	(0.001)	(0.046)	(0.232)	(0.000)	(0.047)	(0.233)
	5.048	3.793	1.858	47.390	10.241	1.725	46.237
	−0.316	1.001	1.096*	−0.804*	1.000	1.100*	−0.805*
PGDP	(0.387)	(0.001)	(0.045)	(0.192)	(0.000)	(0.044)	(0.192)
	0.666	0.627	4.650	88.747	0.100	5.037	88.822
	0.015	1.004	0.980	−0.024*	1.004*	0.980	−0.024*
UNEMP	(2.098)	(0.012)	(0.012)	(0.212)	(0.001)	(0.011)	(0.211)
	0.000	0.143	2.903	23.428	21.264	2.958	23.539
	−3.708*	1.006*	0.989	−0.443*	1.000	0.988	−0.436*
INDPROD	(1.689)	(0.003)	(0.020)	(0.261)	(0.000)	(0.021)	(0.263)
	4.818	4.722	0.298	30.571	0.126	0.359	29.823
	4.520*	0.866*	0.971	−0.381*	0.975	0.939	−0.340*
HOUSING	(1.719)	(0.045)	(0.044)	(0.146)	(0.013)	(0.044)	(0.152)
	6.917	8.827	0.428	88.956	3.669	1.902	77.655

Notes: The table shows the parameter estimates in the forecast regression in Eq. (13) of the professional forecasts on the state space model decomposition, with and without an intercept. Standard errors and Wald test statistics account for the two-step uncertainty and are computed based on the Murphy and Topel (2002) procedure. Standard errors are reported in parentheses, together with Wald test statistics on the null hypothesis that the coefficient is equal to the weight expected in a perfect forecast.

* Indicates that the coefficient differs significantly from the weight expected in a perfect forecast at the 5% significance level.

different from zero. Though the weights for the trend and cycle components of housing starts differ from one significantly in the case of ordinary standard errors, they do not differ from one significantly when we do not include an intercept and account for uncertainty in the estimated components. The weights of the irregular components are still significantly different from one. Remarkably, all of the estimated weights on the irregular components are still negative and some of these effects are still significantly different from zero. The forecast regressions in the last four columns still have a few trend and cycle coefficients that are significantly different from one due to small standard errors; for example, for the nominal GDP, the GDP deflator, and unemployment. In general, the conclusions do not change much when we account for two-step uncertainty. When forecasting one step ahead, the Survey of Professional Forecasters can predict almost all of the variation in the time series due to a trend and a business cycle, but little of the variation caused by the irregular component.

4.3. Analysis of individual forecasts

As was discussed in Section 3, it is difficult to analyse the performances of individual forecasters in the survey, since they have limited histories of responses and their identification numbers may change. However, we can analyze the

Table 9
Forecast regressions ($h = 1$) based on individual forecasts.

	Estimate (std. error)				Estimate (std. error)		
	Intercept	Trend	Cycle	Irreg.	Trend	Cycle	Irreg.
NGDP	−1.213*	1.001*	0.939*	0.253*	1.000*	0.949*	0.248*
	(0.113)	(0.000)	(0.008)	(0.027)	(0.000)	(0.008)	(0.028)
PGDP	−21.752*	1.042*	0.745*	0.055*	1.005*	1.135*	−0.175*
	(0.136)	(0.000)	(0.010)	(0.042)	(0.000)	(0.027)	(0.107)
UNEMP	1.529*	0.995	0.952*	0.628*	1.004*	0.947*	0.635*
	(0.464)	(0.003)	(0.004)	(0.026)	(0.000)	(0.004)	(0.025)
INDPROD	−28.892*	1.054*	0.929*	0.448*	1.003*	0.944*	0.426*
	(0.371)	(0.001)	(0.006)	(0.033)	(0.000)	(0.009)	(0.039)
HOUSING	2.298*	0.922*	0.888*	0.257*	0.970*	0.855*	0.268*
	(0.240)	(0.006)	(0.009)	(0.027)	(0.002)	(0.008)	(0.026)

Notes: The table shows the parameter estimates in the forecast regression in Eq. (13) of the professional forecasts on the low-pass filter decomposition, with and without an intercept. The regressions include all 5784 individual forecasts over the sample period, without averaging over the forecasts from the different panelists in each time period. White standard errors are reported in parentheses, together with Wald test statistics on the null hypothesis that the coefficient is equal to the weight expected in a perfect forecast.
* Indicates that the coefficient differs significantly from the weight expected in a perfect forecast at the 5% significance level.

Table 10
Forecast regressions based on a spectral analysis for $h = 5$.

	Estimate (std. error)				Estimate (std. error)		
	Intercept	Trend	Cycle	Irreg.	Trend	Cycle	Irreg.
NGDP	−3.338	1.004	0.040*	−0.118*	1.000	−0.061*	−0.098*
	(3.144)	(0.004)	(0.142)	(0.451)	(0.000)	(0.135)	(0.462)
	1.127	1.203	54.006	6.133	0.404	62.255	5.650
PGDP	3.543	0.995	0.742	0.166*	1.000*	0.805	−0.201*
	(3.752)	(0.006)	(0.162)	(0.497)	(0.000)	(0.143)	(0.493)
	0.892	0.767	2.543	5.500	6.259	1.852	5.946
UNEMP	9.921	0.945	0.139*	−0.501*	0.999	0.103*	−0.446*
	(9.295)	(0.052)	(0.115)	(0.436)	(0.005)	(0.108)	(0.436)
	1.139	1.110	56.251	11.855	0.018	68.515	10.978
INDPROD	−10.240	1.019	−0.119*	0.089*	1.002*	−0.117*	0.087*
	(7.682)	(0.013)	(0.098)	(0.393)	(0.001)	(0.101)	(0.392)
	1.777	2.104	129.042	5.376	12.459	123.125	5.435
HOUSING	20.545*	0.553*	0.076*	−0.012*	1.000	−0.406*	0.107*
	(2.756)	(0.065)	(0.115)	(0.195)	(0.023)	(0.105)	(0.308)
	55.579	46.629	64.149	26.838	0.000	178.401	8.389

Notes: The table shows the parameter estimates in the forecast regression in Eq. (13), with $h = 5$, of the professional forecasts on the low-pass filter decomposition, with and without an intercept. Due to missing values, the estimation sample starts at 1974Q4. White standard errors are reported in parentheses, together with Wald test statistics on the null hypothesis that the coefficient is equal to the weight expected in a perfect forecast.
* Indicates that the coefficient differs significantly from the weight expected in a perfect forecast at the 5% significance level.

individual predictions by pooling them all in one forecast regression. Table 9 shows the results of a forecast regression on all individual forecasts, that is, all forecasts over the sample period, without averaging over the forecasts from the different panelists in each time period.

We find that the weights that correspond to the trend and the cycle are also close to one when we consider all individual forecasts, instead of the mean of the survey. In most cases, the estimated parameter of the irregular component is closer to zero than to one. Since the regressions include a large number of observations (5784), the standard errors become small and almost every weight is significantly different from the weight in a perfect forecast at the 5% significance level.[3] In summary, the findings are in line with the results based on the mean of the Survey of Professional Forecasters.

4.4. Multi-step-ahead forecasts

So far, our results have been based on the one-step-ahead predictions from the Survey of Professional Forecasters. We examine whether our findings also hold for multi-step-ahead forecasts by performing the forecast regressions for different forecast horizons. The Survey of Professional Forecasters provides forecasts for up to five quarters ahead.

Table 10 shows the results of the forecast regressions for $h = 5$ based on spectral analysis. Appendix D shows

3 Unreported results show that a weighted regression where we weight using the number of forecasters to account for time variation in the number of forecasters produces similar results. These results can be obtained from the authors upon request.

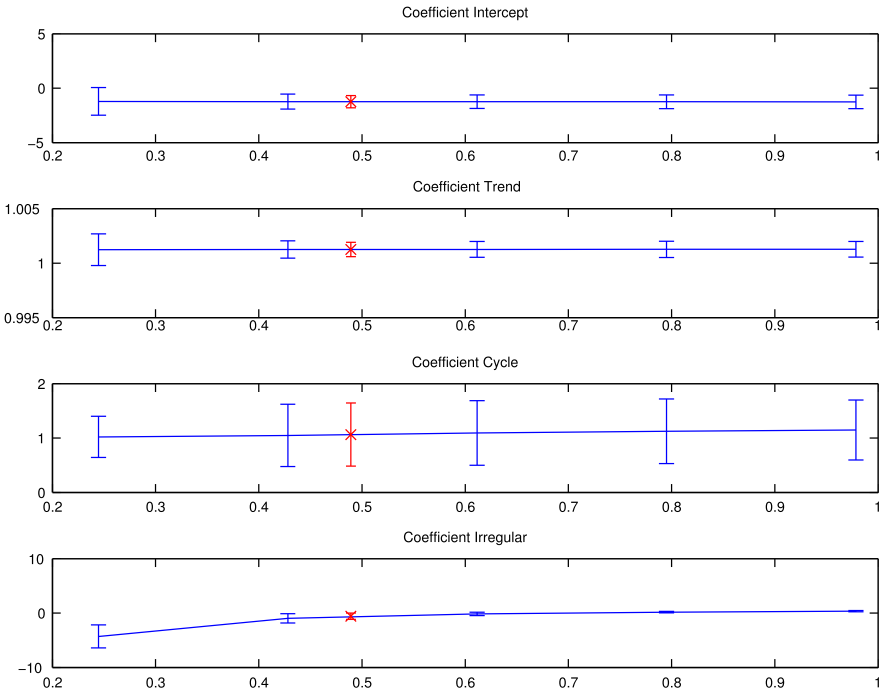

Fig. 3. Sensitivity analysis: fixed variance irregular component. Sensitivity of the estimated coefficients in the forecast regression of the nominal GDP to the standard deviation of the estimated irregular component in the state space framework. The (blue) lines show the values of the estimated coefficients with error bands of one standard error, for different values of the standard deviation of the estimated irregular component. The error bands are constructed with two-step standard errors. The (red) asterisks show the estimated coefficients at the value of the standard deviation of the estimated irregular component in the low-pass filter.

the results for $h = 2, \ldots, 4$. We find that, for all forecast horizons, the trend component receives a weight that is close to one and the weights that correspond to the irregular component are closer to zero than to one. The parameter estimates that correspond to the cycle decrease with the forecast horizon, and the forecast bias increases in the forecast horizon. In summary, we find that the professional forecasters are able to predict the trend over a longer horizon, but the forecasters are less able to produce unbiased forecasts and capture variation in the business cycle when the forecast horizon increases.

5. Further results

This section performs some extra analyses in order to shed further light on our results and provide additional insights into the value of the professional forecasts. First, we assess the robustness of the fixed variance of the irregular component in the state space framework to a range of values. Next, we compare the forecasts of a basic time series model with the professional forecasts with respect to both their ability to forecast the irregular component and accuracy. Finally, we examine the forecast regression in Section 4.2 with lagged trend, cycle and irregular components.

5.1. Sensitivity to a fixed variance

We estimate the components in the state space framework by fixing the variance of the irregular component to the value of the variance of the estimated irregular component in the low-pass filter. To assess how the forecast regression results are affected by this restriction, we perform a sensitivity analysis on the value of the variance of the irregular component. Fig. 3 shows the sensitivity of the estimated coefficients in the forecast regression on the nominal GDP based on the estimated components in the state space model. Figs. E.1–E.4 in Appendix E show the sensitivities for the other time series.

Fig. 3 shows the values of the estimated coefficients with error bands of one standard error, for different values of the standard deviation of the estimated irregular component. The asterisks show the estimated coefficients at the value of the standard deviation of the estimated irregular component in the low-pass filter. The coefficients of the intercept, trend, and business cycle show hardly any differences over the interval, whereas the coefficient of the irregular component seems to deviate more from the weight expected in a perfect forecast as the standard deviation of the estimated irregular component decreases. Thus, the decision to fix the variance of the irregular component is not likely to influence the results found in the forecast regressions.

5.2. Model-based forecast decomposition

Based on the forecast regressions, we find that the mean of the Survey of Professional Forecasters explains only a little of the time series variation due to the irregular

Table 11
$AR(p)$ model forecast regressions ($h = 1$) for the nominal GDP.

	Estimate (std. error)				Estimate (std. error)		
	Intercept	Trend	Cycle	Irreg.	Trend	Cycle	Irreg.
NGDP	−2.154* (0.783) 7.572	1.002* (0.001) 7.565	0.971 (0.051) 0.321	0.010* (0.163) 36.643	1.000 (0.000) 0.497	0.980 (0.054) 0.138	0.009* (0.172) 33.031
PGDP	−1.222 (0.778) 2.466	1.002 (0.001) 2.449	0.983 (0.061) 0.078	−0.117* (0.315) 12.618	1.000 (0.000) 0.054	0.996 (0.060) 0.003	−0.122* (0.321) 12.172
UNEMP	2.439 (4.348) 0.315	0.986 (0.024) 0.351	1.029 (0.047) 0.386	−0.026* (0.351) 8.520	0.999 (0.002) 0.178	1.023 (0.046) 0.244	−0.015* (0.349) 8.462
INDPROD	−1.322 (3.039) 0.189	1.002 (0.006) 0.187	1.055 (0.054) 1.042	0.309* (0.251) 7.582	1.000 (0.000) 0.036	1.055 (0.054) 1.045	0.309* (0.250) 7.638
HOUSING	1.834 (1.370) 1.792	0.962 (0.031) 1.455	1.032 (0.062) 0.260	0.024* (0.170) 33.081	1.003 (0.017) 0.029	0.991 (0.060) 0.022	0.034* (0.173) 31.051

Notes: The table shows the parameter estimates in the forecast regression in Eq. (13) of the $AR(p)$ model forecasts on the low-pass filter decomposition, with and without an intercept. White standard errors are reported in parentheses, together with Wald test statistics on the null hypothesis that the coefficient is equal to the weight expected in a perfect forecast.

* Indicates that the coefficient differs significantly from the weight expected in a perfect forecast at the 5% significance level.

Table 12
Mean squared prediction errors.

	Last 40 quarters			Last 20 quarters		
	SPF	SSM	DM	SPF	SSM	DM
NGDP	0.749	0.884	−3.618*	0.830	0.844	−0.194
PGDP	0.554	0.562	−0.731	0.573	0.584	−0.503
UNEMP	2.299	4.462	−5.739*	1.972	4.508	−2.387*
INDPROD	1.136	1.453	−2.521*	0.816	1.171	−1.216
HOUSING	6.516	8.673	−3.706*	7.083	9.082	−1.246

Notes: The table shows the mean squared prediction errors of the one-step-ahead predictions of the Survey of Professional Forecasters (SPF) and the state space model (SSM), together with Diebold and Mariano (1995) test statistics. We have real-time data from 1947Q1 to 2014Q1, from which the state space model uses an expanding window to predict the last 40 quarters. Mean squared prediction errors are reported both over all predictions and over the predictions for the last 20 quarters.

* Indicates that the difference in forecast accuracy is significant at the 5% significance level.

component. This is surprising given the assumption that professional forecasters should adapt more quickly and be more flexible than pure model-based prediction methods. However, we do not expect an econometric model to capture the irregular component. To investigate this conjecture, we regress model forecasts on the estimated components of the historical time series.

We generate forecasts using an autoregressive model of order p, $AR(p)$, for the first difference of the log series estimated on a moving window of ten years of quarterly observations. The order p is selected for each forecasting period by means of the Schwartz information criterion on the moving window. The model is estimated using the latest vintage of real-time historical data available at the moment of forecasting using an approach similar to that in the previous section.

Table 11 shows the forecast regression results of the one-step-ahead predictions in the sample from the last quarter of 1971 to the first quarter of 2013. The overall picture resembles the results in Section 4.2. The weights of the components, whether estimated using the spectral analysis or the state space model, show that the model-based predictions can only explain the trend and cycle components. The forecasts do not contain any information about the irregular component, and the weight is negative if one opts for a state space model approach to decomposing the time series.

5.3. Forecast accuracy

Our previous results have shown that the professional forecasters predict little of the irregular component. We investigate the value added by professional forecasts by comparing them to simple model-based predictions, which we obtain from the Kalman filter in the state space model in Eqs. (6)–(10), where we do not fix the signal-to-noise ratio. Thus, the irregular component estimated by the state space model is allowed to go to zero.

We generate the one-step-ahead predictions in the sample from 1980Q4 to 2014Q2 using an expanding window that consists of the latest vintage of real-time historical data that is available at the moment of forecasting. The first estimation sample starts at 1947Q1. The data is from the Real-Time Data Set for Macroeconomists of the Federal Reserve Bank of Philadelphia. We account for changing base years in the GDP deflator and the industrial

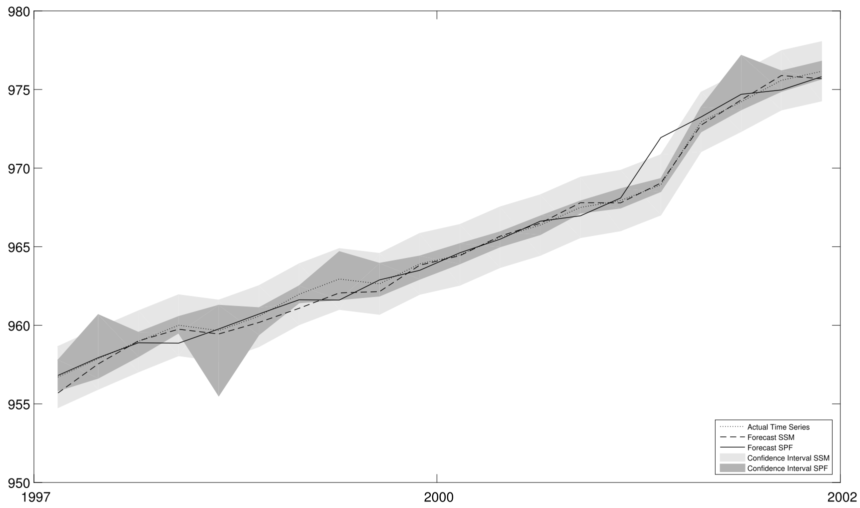

Fig. 4. Model-based and professional forecasts: NGDP. Nominal GDP predictions of the state space model (dashed line) and the Survey of Professional Forecasters (dash-dotted line), together with the actual time series (solid line). The corresponding gray surfaces represent the constructed confidence intervals of the predictions. The jump in 2013 is due to a change in the Bureau of Economic Analysis' (BEA) definition of the GDP.

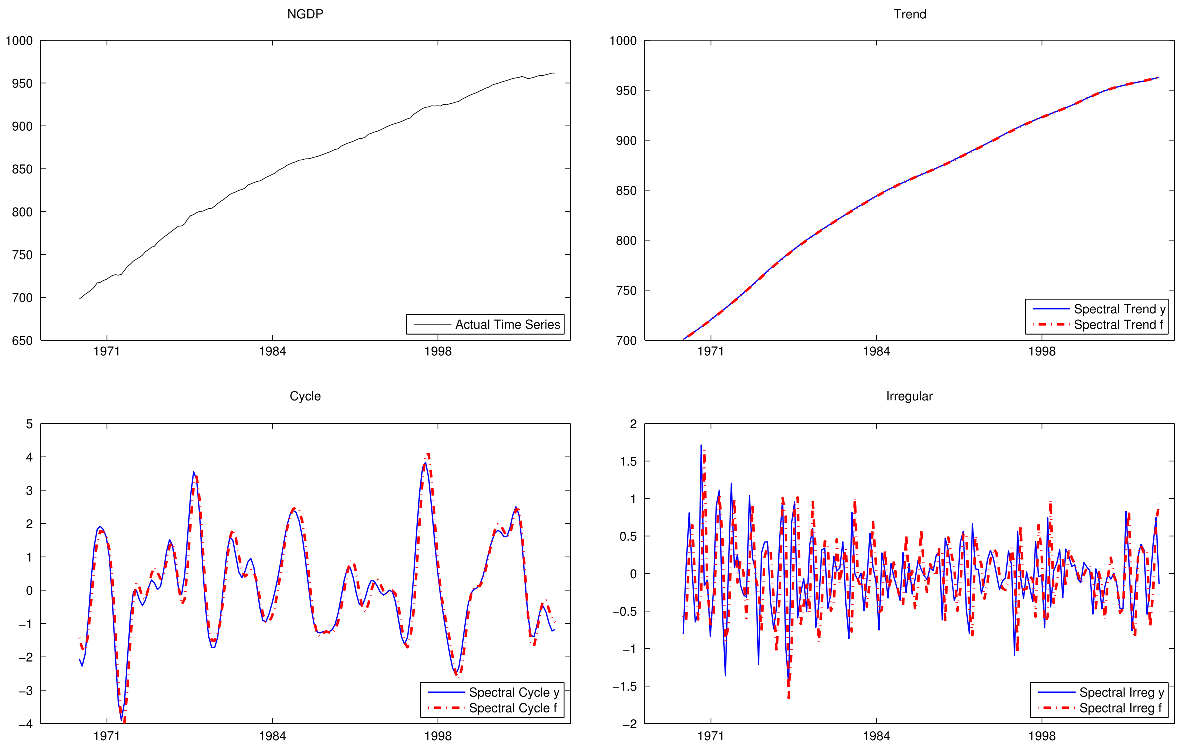

Fig. 5. Decomposition of the nominal GDP in a spectral analysis. The historical time series and the mean of the forecasts of the Survey of Professional Forecasters for the nominal GDP decomposed by the low-pass filters into a trend, a cycle, and an irregular component. The first panel shows one hundred times the logarithm of the actual values of the historical time series, while the other panels show the estimated components of the actual historical time series by a blue solid line and the estimated components of the mean of the forecasts of the Survey of Professional Forecasters by a red dash-dotted line.

production index by scaling all of the data in both the Real-Time Data Set and the Survey of Professional Forecasters by the value for 1980Q4 from the latest vintage available at the moment of forecasting.

Table 12 shows the mean squared prediction errors for the forecasts of both the state space model and the Survey of Professional Forecasters. With the exception of PGDP, the state space model is outperformed significantly at the

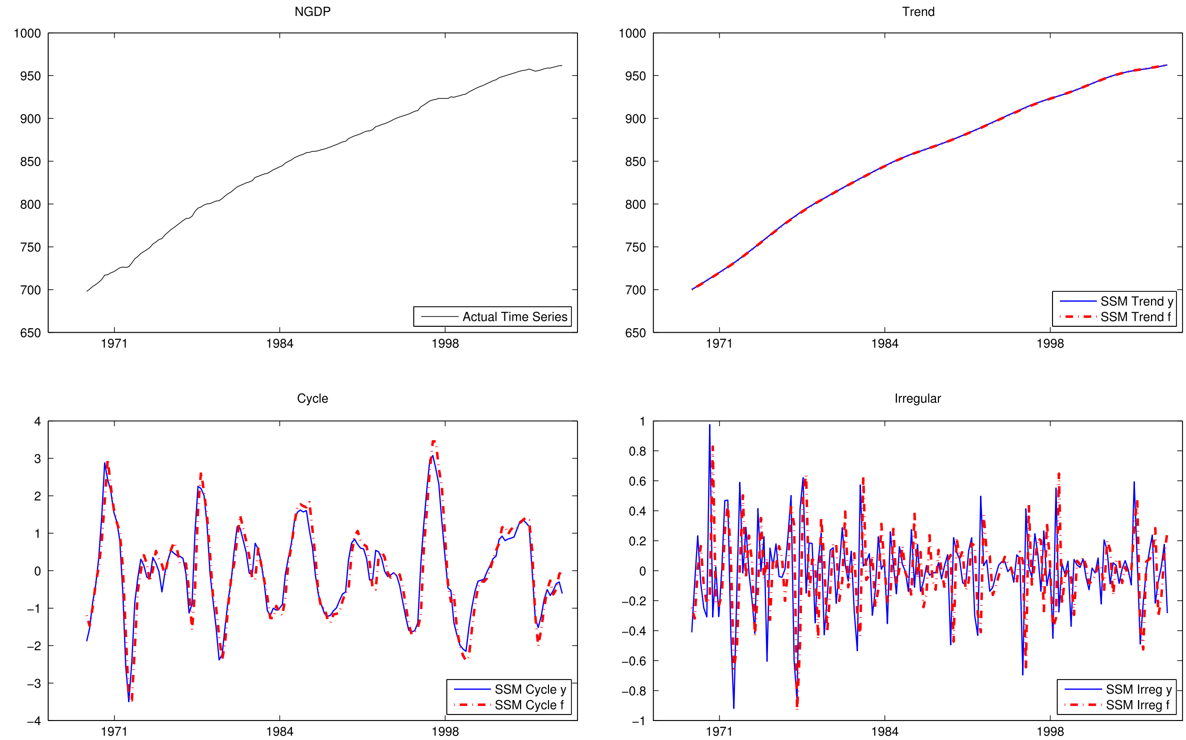

Fig. 6. Decomposition of the nominal GDP in a state space model. The historical time series and the mean of the forecasts of the Survey of Professional Forecasters for the nominal GDP decomposed by the state space model into a trend, a cycle, and an irregular component. The first panel shows one hundred times the logarithm of the actual values of the historical time series, while the other panels show the estimated components of the actual historical time series by a blue solid line and the estimated components of the mean of the forecasts of the Survey of Professional Forecasters by a red dash-dotted line.

Table 13
Forecast regressions ($h = 1$) on the lagged estimated components.

	Estimate (std. error)				Estimate (std. error)		
	Intercept	Trend	Cycle	Irreg.	Trend	Cycle	Irreg.
NGDP	6.610*	0.994*	0.989	0.951	1.002*	0.958	0.953
	(0.495)	(0.001)	(0.025)	(0.094)	(0.000)	(0.041)	(0.155)
	178.283	110.964	0.207	0.272	610.593	1.081	0.092
PGDP	−9.641*	1.022*	0.998	1.002	1.002*	1.008	0.999
	(1.029)	(0.002)	(0.006)	(0.010)	(0.000)	(0.004)	(0.007)
	87.871	100.860	0.136	0.054	487.419	3.751	0.020
UNEMP	−3.270	1.024	0.896*	0.541	1.006*	0.905*	0.528
	(3.554)	(0.020)	(0.031)	(0.247)	(0.002)	(0.029)	(0.247)
	0.847	1.459	11.560	3.462	12.175	10.747	3.657
INDPROD	0.245	1.001	0.974*	0.943	1.001*	0.974*	0.943
	(4.915)	(0.010)	(0.013)	(0.031)	(0.000)	(0.013)	(0.031)
	0.002	0.004	4.268	3.425	38.798	4.319	3.385
HOUSING	−0.123	0.971	0.866*	0.558*	0.968*	0.868*	0.557*
	(0.863)	(0.021)	(0.033)	(0.077)	(0.009)	(0.032)	(0.077)
	0.020	1.986	16.395	32.577	13.202	16.674	33.377

Notes: The table shows the parameter estimates in the forecast regression in Eq. (13) of the professional forecasts on the lagged values of the low-pass filter decomposition, with and without an intercept. White standard errors are reported in parentheses, together with Wald test statistics on the null hypothesis that the coefficient is equal to the weight expected in a perfect forecast.

* Indicates that the coefficient differs significantly from the weight expected in a perfect forecast at the 5% significance level.

5% significance level by the professional forecasters based on all predictions. Although the professional forecasters cannot capture all of the variation in the irregular component, they probably do a better job of forecasting the trend and the business cycle than the state space model over the full time period. When we only consider the predictions for the last 20 quarters, the state space model is significantly outperformed only for unemployment, but again the professional forecasters are more accurate in terms of MSPE.

Fig. 4 shows the nominal GDP forecasts,[4] the confidence intervals and the actual historical time series for the evaluation period that includes the last five years of the sample. The confidence interval for the Survey of Professional Forecasters is constructed from the lowest and highest individual forecasts, while the state space prediction comes along with a covariance matrix from which we retrieve two times the standard deviation. The two predictions are very close to each other and follow almost identical patterns. While the confidence interval constructed for the professional forecasts seems narrower over the evaluation period as a whole, it does have some outliers, whereas the confidence interval of the state space predictions is quite stable. Overall, the predictions produced by the structural time series model are almost the same as those from the Survey of Professional Forecasters.

5.4. Forecast regression with lagged components

We shed light on the information in the professional forecasts by now also considering the time series decomposition of their mean. Figs. 5 and 6 show these decompositions, together with the decomposition of the historical time series based on a spectral analysis and a state space model, respectively. In both figures, the business cycle and irregular components estimated from the forecasts seem to lag behind those estimated from the historical time series.

Since the decompositions of the mean of the forecasts of the Survey of Professional forecasters suggest that the forecasts are biased towards lagged values of the nominal GDP, we regress the professional forecasts on the lagged values of the components estimated from the historical time series. Table 13 shows the results for all series. Due to the small standard errors, the weights of the lagged estimated trend and cycle sometimes differ significantly from one, but the weights of the irregular component do not differ significantly from one, except for housing starts. This suggests that the professional forecasters explain the value of the series in the current period, which has already been published, instead of explaining irregular events in the future.

6. Conclusion

This paper has examined what professional forecasters actually explain. We use a spectral analysis and a state space model to decompose economic time series into three components: a trend, a business cycle, and an irregular component. We then examine which components are explained by the Survey of Professional Forecasters in a regression of the mean forecasts on the estimated components of the actual historical time series. These regressions are run based on the components estimated by the low-pass filters in the spectral analysis and the components estimated in a state space model. The two approaches lead to approximately the same results. For most time series, we cannot reject that the mean of the professional forecasts predicts the variation in the trend and the business cycle, but there is little or no predictive power for the variation in the irregular component. A simple state space model, such as is used commonly for estimating trends and cycles in time series, produces almost the same predictions.

The results suggest that neither econometric models nor the mean of the professional forecasts contain much information about the variation in the irregular component. This result is not surprising when professional forecasters also use model-based techniques to construct their predictions and the irregular component is characterized by weak persistence. Both econometric models and professional forecasters perform well for capturing the trend and the business cycle. The fact that the professional forecasters also capture a small amount of the variation in the irregular components in some cases may explain why some businesses and policymakers rely on professional forecasters.

Since the time series in the database of the Survey of Professional Forecasters are already seasonally adjusted, the time series decompositions are limited to a trend, a cycle and an irregular component. An interesting topic for future research could be to analyze whether professional forecasters are able to predict seasonal variation by extending our analysis using a seasonal component and seasonally unadjusted data.

Acknowledgments

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Appendix A. Time series decompositions

Section 4.1 shows the decomposition of the nominal GDP into a trend, a cycle, and an irregular component using the low-pass filters and the state space model. Figs. A.1–A.4 show the decompositions of the other variables: the GDP deflator (PGDP), unemployment (UNEMP), the industrial production index (INDPROD), and housing starts (HOUSING). Each figure, corresponding to a variable, consists of four panels. The first panel shows the actual values in the historical time series, while the other panels show the components estimated in the low-pass filters by a blue solid line and the components estimated in the state space model by a red dash-dotted line. All variables are log-transformed and multiplied by 100.

[4] The jump in 2013 shown in Fig. 4 is due to a change in the Bureau of Economic Analysis' (BEA) definition of the GDP. However, our results are robust to these kind of changes, as the analysis of the first differences of the series in Table 6 shows. We thank an anonymous referee for pointing this out.

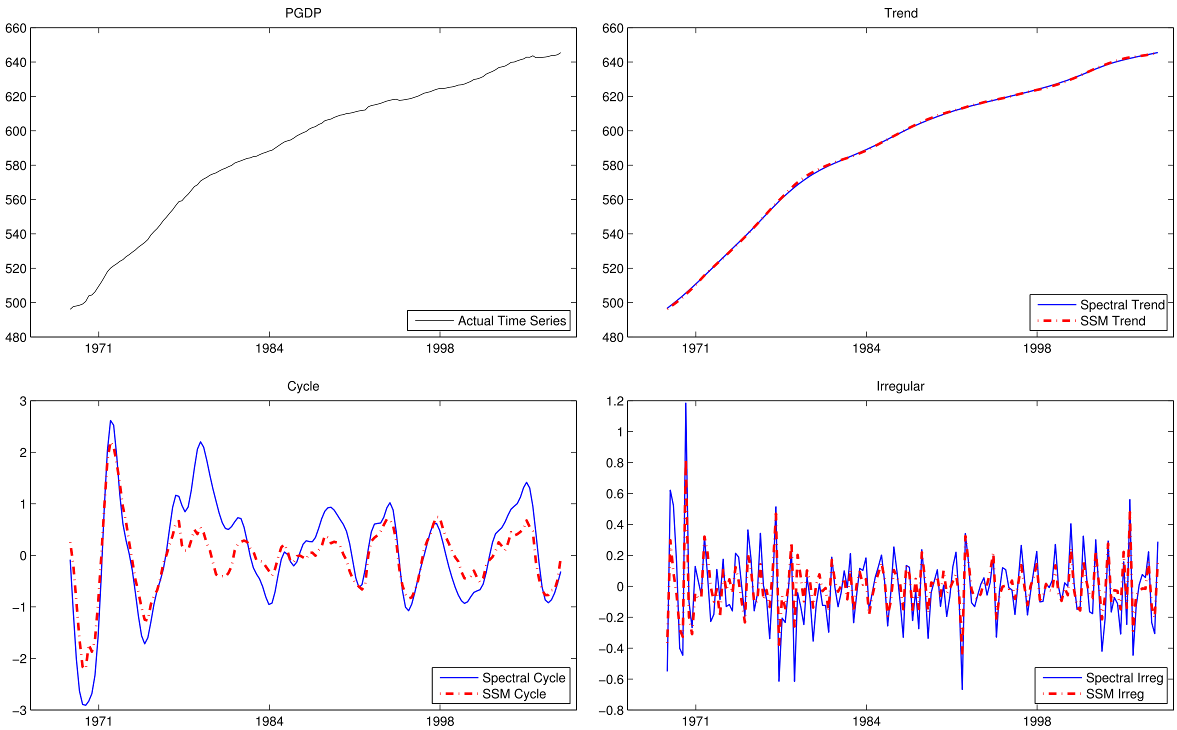

Fig. A.1. GDP deflator.

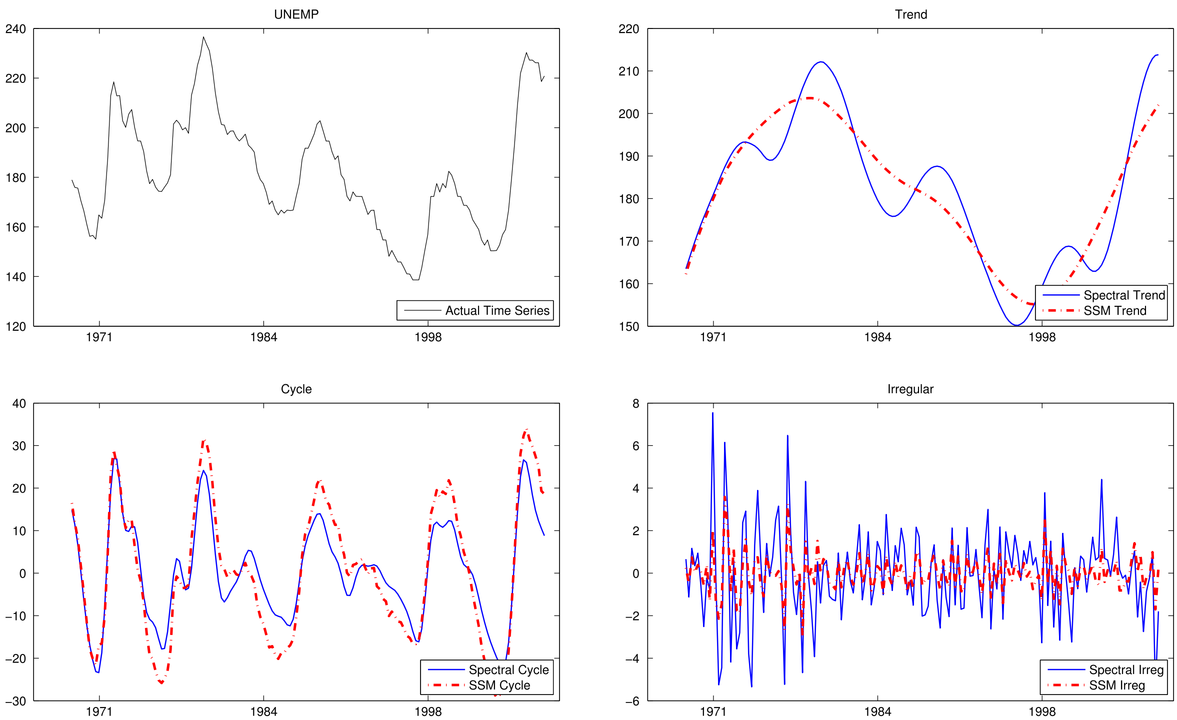

Fig. A.2. Unemployment.

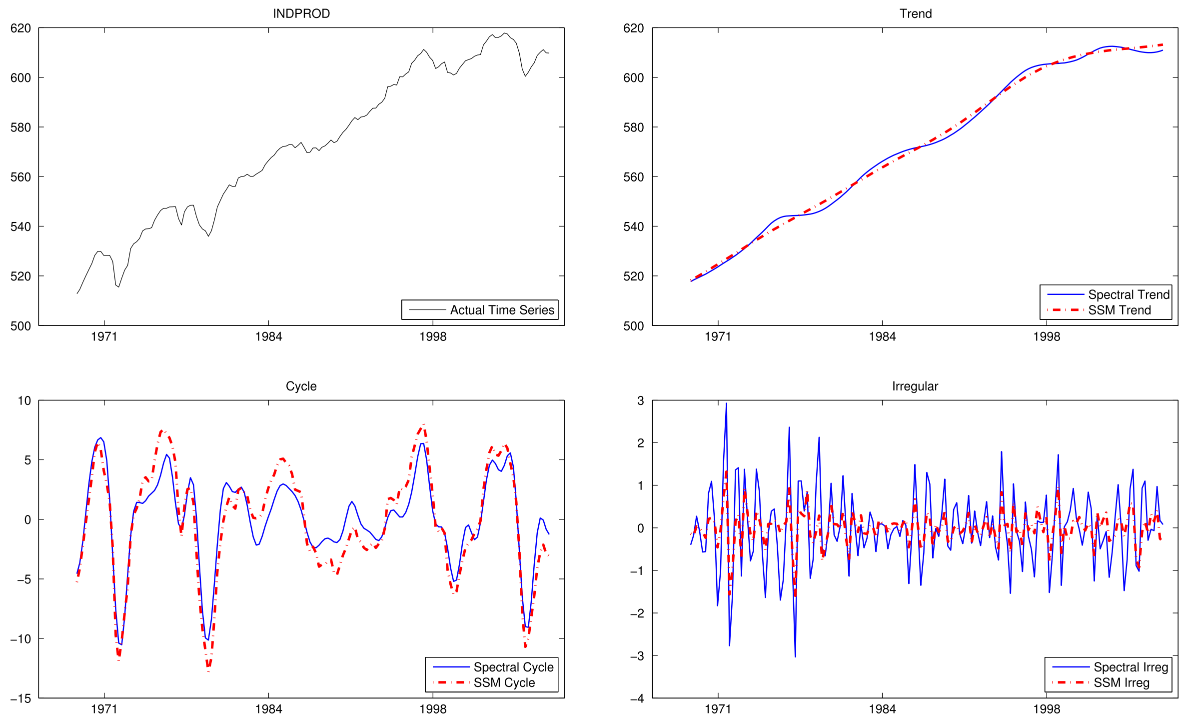

Fig. A.3. Industrial production index.

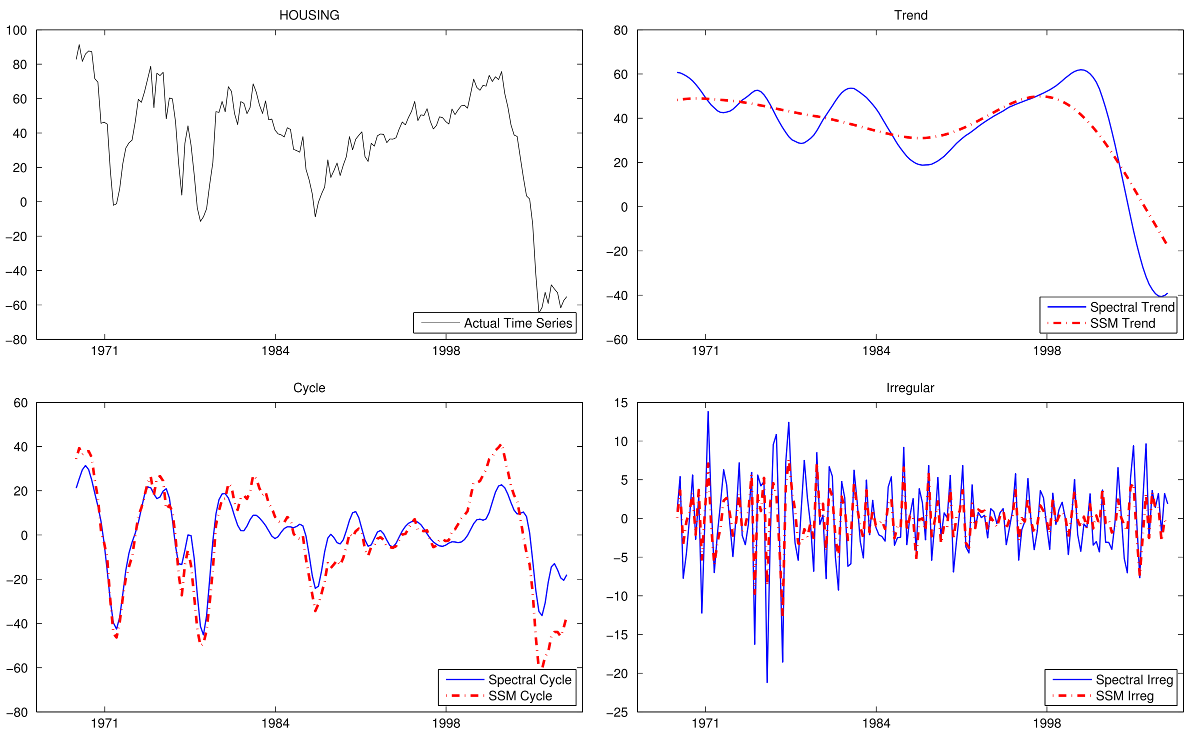

Fig. A.4. Housing starts.

Appendix B. Alternative frequency filters

See Table B.1.

Table B.1
Forecast regressions ($h = 1$) based on alternative frequency filters.

	Estimate (std. error)				Estimate (std. error)		
	Intercept	Trend	Cycle	Irreg.	Trend	Cycle	Irreg.
	Christiano-Fitzgerald filter						
NGDP	−0.749 (0.482) 2.420	1.001 (0.001) 1.514	0.969 (0.036) 0.715	0.182* (0.138) 35.188	1.000* (0.000) 11.163	0.971 (0.037) 0.639	0.182* (0.140) 34.043
PGDP	−0.729 (0.376) 3.759	1.001 (0.001) 3.646	1.003 (0.040) 0.004	−0.139* (0.158) 51.905	1.000 (0.000) 1.070	1.001 (0.042) 0.000	−0.138* (0.168) 46.166
UNEMP	1.280 (1.404) 0.832	0.997 (0.008) 0.128	0.959* (0.014) 9.073	0.508* (0.099) 24.839	1.004* (0.001) 20.765	0.958* (0.014) 9.328	0.508* (0.100) 24.370
INDPROD	−1.451 (1.493) 0.944	1.003 (0.003) 0.935	0.953 (0.024) 3.687	0.425* (0.162) 12.654	1.000 (0.000) 0.016	0.954 (0.024) 3.594	0.426* (0.161) 12.777
HOUSING	1.232 (0.661) 3.471	0.944* (0.014) 16.455	0.908* (0.027) 11.897	0.230* (0.115) 44.493	0.964* (0.008) 19.145	0.908* (0.027) 11.768	0.230* (0.116) 44.338
	Butterworth filter						
NGDP	−0.753 (0.475) 2.515	1.001 (0.001) 1.580	1.004 (0.039) 0.010	0.017* (0.170) 33.365	1.000* (0.000) 11.735	1.004 (0.040) 0.013	0.017* (0.172) 32.490
PGDP	−0.716* (0.363) 3.881	1.001 (0.001) 3.762	1.038 (0.040) 0.892	−0.320* (0.152) 75.130	1.000 (0.000) 1.164	1.039 (0.041) 0.882	−0.320* (0.162) 66.659
UNEMP	0.678 (1.735) 0.153	1.001 (0.009) 0.004	0.961* (0.016) 5.672	0.457* (0.102) 28.376	1.004* (0.001) 21.873	0.959* (0.016) 6.988	0.458* (0.102) 27.953
INDPROD	−1.476 (1.483) 0.991	1.003 (0.003) 0.983	0.959 (0.030) 1.945	0.330* (0.198) 11.433	1.000 (0.000) 0.016	0.959 (0.030) 1.806	0.329* (0.198) 11.496
HOUSING	1.168 (0.680) 2.953	0.946* (0.015) 12.278	0.928* (0.036) 4.001	0.095* (0.139) 42.503	0.967* (0.009) 14.606	0.916* (0.036) 5.458	0.099* (0.138) 42.474

Notes: The table shows the parameter estimates in the forecast regression in Eq. (13) of the professional forecasts on the Christiano-Fitzgerald filter decomposition and the Butterworth filter decomposition, with and without an intercept. White standard errors are reported in parentheses, together with Wald test statistics on the null hypothesis that the coefficient is equal to the weight expected in a perfect forecast.
* Indicates that the coefficient differs significantly from the weight expected in a perfect forecast at the 5% significance level.

Appendix C. Forecast regressions on first differences

See Table C.1.

Table C.1
Forecast regressions ($h = 1$) based on a spectral analysis on first differences.

	Estimate (std. error)			Estimate (std. error)	
	Intercept	Cycle	Irreg.	Cycle	Irreg.
NGDP	0.430* (0.071) 36.544	0.646* (0.043) 68.780	0.169* (0.056) 216.222	0.847* (0.019) 62.220	0.171* (0.063) 174.791
PGDP	0.356* (0.043) 68.330	0.619* (0.048) 63.377	−0.002* (0.085) 138.426	0.848* (0.031) 24.196	−0.002* (0.119) 71.160
UNEMP	0.852* (0.122) 48.381	0.761* (0.030) 63.980	0.518* (0.054) 80.745	0.770* (0.033) 47.402	0.517* (0.064) 56.536

(continued on next page)

Table C.1 (*continued*)

	Estimate (std. error)			Estimate (std. error)	
	Intercept	Cycle	Irreg.	Cycle	Irreg.
INDPROD	0.247*	0.531*	0.221*	0.577*	0.222*
	(0.073)	(0.040)	(0.077)	(0.037)	(0.083)
	11.443	135.813	102.068	129.573	87.411
HOUSING	−0.953*	0.444*	0.361*	0.468*	0.362*
	(0.334)	(0.052)	(0.053)	(0.053)	(0.054)
	8.152	112.131	143.583	102.285	140.718

Notes: The table shows the parameter estimates in the forecast regression in Eq. (13), with first differences of the series instead of levels, of the professional forecasts on the low-pass filter decomposition, with and without an intercept. Since we are taking first differences, the trend is removed from the forecast regression. White standard errors are reported in parentheses, together with Wald test statistics on the null hypothesis that the coefficient is equal to the weight expected in a perfect forecast.

* Indicates that the coefficient differs significantly from the weight expected in a perfect forecast at the 5% significance level.

Appendix D. Multi-step-ahead forecasts

See Tables D.1–D.3.

Table D.1
Forecast regressions based on a spectral analysis for $h = 2$.

	Estimate (std. error)				Estimate (std. error)		
	Intercept	Trend	Cycle	Irreg.	Trend	Cycle	Irreg.
NGDP	−2.317*	1.002*	0.820*	−0.362*	1.000*	0.827*	−0.374*
	(0.933)	(0.001)	(0.065)	(0.196)	(0.000)	(0.066)	(0.207)
	6.168	4.999	7.640	48.545	9.255	6.857	44.203
PGDP	−1.085	1.002	0.991	−0.504*	1.000	1.002	−0.520*
	(0.941)	(0.002)	(0.059)	(0.227)	(0.000)	(0.062)	(0.236)
	1.331	1.290	0.024	43.901	0.514	0.001	41.508
UNEMP	3.951	0.984	0.812*	−0.227*	1.006*	0.800*	−0.211*
	(3.758)	(0.021)	(0.035)	(0.222)	(0.002)	(0.033)	(0.221)
	1.105	0.546	29.244	30.634	8.066	37.562	30.036
INDPROD	−4.779	1.009	0.766*	−0.207*	1.000	0.765*	−0.210*
	(3.456)	(0.006)	(0.053)	(0.246)	(0.000)	(0.053)	(0.240)
	1.913	2.025	19.653	24.055	0.837	19.796	25.360
HOUSING	6.323*	0.852*	0.638*	−0.300*	0.986	0.537*	−0.268*
	(1.247)	(0.031)	(0.060)	(0.129)	(0.015)	(0.056)	(0.128)
	25.722	22.887	36.707	102.017	0.865	69.448	98.129

Notes: The table shows the parameter estimates in the forecast regression in Eq. (13), with $h = 2$, of the professional forecasts on the low-pass filter decomposition, with and without an intercept. White standard errors are reported in parentheses, together with Wald test statistics on the null hypothesis that the coefficient is equal to the weight expected in a perfect forecast.

* Indicates that the coefficient differs significantly from the weight expected in a perfect forecast at the 5% significance level.

Table D.2
Forecast regressions based on a spectral analysis for $h = 3$.

	Estimate (std. error)				Estimate (std. error)		
	Intercept	Trend	Cycle	Irreg.	Trend	Cycle	Irreg.
NGDP	−3.557*	1.004*	0.589*	−0.396*	1.000*	0.594*	−0.413*
	(1.240)	(0.001)	(0.094)	(0.257)	(0.000)	(0.093)	(0.267)
	8.222	7.104	19.319	29.536	4.436	18.917	27.960
PGDP	−2.924	1.005	0.961	−0.517*	1.000	0.989	−0.531*
	(1.524)	(0.003)	(0.095)	(0.318)	(0.000)	(0.102)	(0.346)
	3.679	3.723	0.170	22.740	0.187	0.011	19.523
UNEMP	4.160	0.981	0.632*	−0.336*	1.004	0.620*	−0.318*
	(5.931)	(0.033)	(0.060)	(0.323)	(0.003)	(0.058)	(0.322)
	0.492	0.310	37.578	17.080	1.776	43.577	16.758
INDPROD	−4.581	1.009	0.507*	−0.451*	1.001	0.506*	−0.455*
	(4.816)	(0.008)	(0.074)	(0.299)	(0.000)	(0.074)	(0.293)
	0.905	1.072	44.229	23.500	3.630	45.111	24.704
HOUSING	10.425*	0.790*	0.387*	−0.277*	1.010	0.220*	−0.227*
	(1.739)	(0.042)	(0.076)	(0.156)	(0.018)	(0.069)	(0.166)
	35.925	25.219	64.405	66.677	0.340	128.258	54.812

Notes: The table shows the parameter estimates in the forecast regression in Eq. (13), with $h = 3$, of the professional forecasts on the low-pass filter decomposition, with and without an intercept. White standard errors are reported in parentheses, together with Wald test statistics on the null hypothesis that the coefficient is equal to the weight expected in a perfect forecast.

* Indicates that the coefficient differs significantly from the weight expected in a perfect forecast at the 5% significance level.

Table D.3
Forecast regressions based on a spectral analysis for $h = 4$.

	Estimate (std. error)				Estimate (std. error)		
	Intercept	Trend	Cycle	Irreg.	Trend	Cycle	Irreg.
	−4.839*	1.005*	0.283*	−0.134*	1.000	0.285*	−0.138*
NGDP	(1.507)	(0.002)	(0.105)	(0.279)	(0.000)	(0.104)	(0.296)
	10.313	9.321	46.936	16.468	1.505	46.996	14.797
	−5.390*	1.009*	0.891	−0.422*	1.000	0.936	−0.404*
PGDP	(2.160)	(0.004)	(0.134)	(0.386)	(0.000)	(0.150)	(0.428)
	6.226	6.395	0.663	13.591	0.037	0.185	10.790
	5.300	0.971	0.413*	−0.357*	1.000	0.397*	−0.336*
UNEMP	(7.917)	(0.044)	(0.085)	(0.382)	(0.004)	(0.080)	(0.381)
	0.448	0.417	48.170	12.636	0.007	56.375	12.272
	−3.291	1.007	0.223*	−0.084*	1.001*	0.222*	−0.087*
INDPROD	(5.810)	(0.010)	(0.085)	(0.320)	(0.000)	(0.084)	(0.316)
	0.321	0.487	84.426	11.484	8.790	86.014	11.840
	15.014*	0.715*	0.171*	−0.090*	1.032	−0.072*	−0.012*
HOUSING	(2.164)	(0.051)	(0.081)	(0.161)	(0.020)	(0.073)	(0.202)
	48.149	31.553	104.963	45.799	2.492	213.014	25.032

Notes: The table shows the parameter estimates in the forecast regression in Eq. (13), with $h = 4$, of the professional forecasts on the low-pass filter decomposition, with and without an intercept. White standard errors are reported in parentheses, together with Wald test statistics on the null hypothesis that the coefficient is equal to the weight expected in a perfect forecast.
* Indicates that the coefficient differs significantly from the weight expected in a perfect forecast at the 5% significance level.

Appendix E. Sensitivity analysis

Section 4.2 showed the sensitivity of the estimated coefficients in the forecast regression of the nominal GDP to the standard deviation of the variance of the estimated irregular component in the state space framework. Figs. E.1–E.4 show the sensitivities of the coefficients of the components of the other variables: the GDP deflator (PGDP), unemployment (UNEMP), the industrial production index (INDPROD), and housing starts (HOUSING). Each figure, corresponding to a variable, consists of four panels: the coefficients of the intercept, trend, business cycle, and irregular components. The blue lines indicate the value of the estimated coefficient, with error bands of one standard error, for different values of the standard deviation of the variance of the estimated irregular component. The error bands are constructed using two-step standard errors. The red asterisks show the estimated coefficient at the value of the standard deviation of the variance of the estimated irregular component in the low-pass filter.

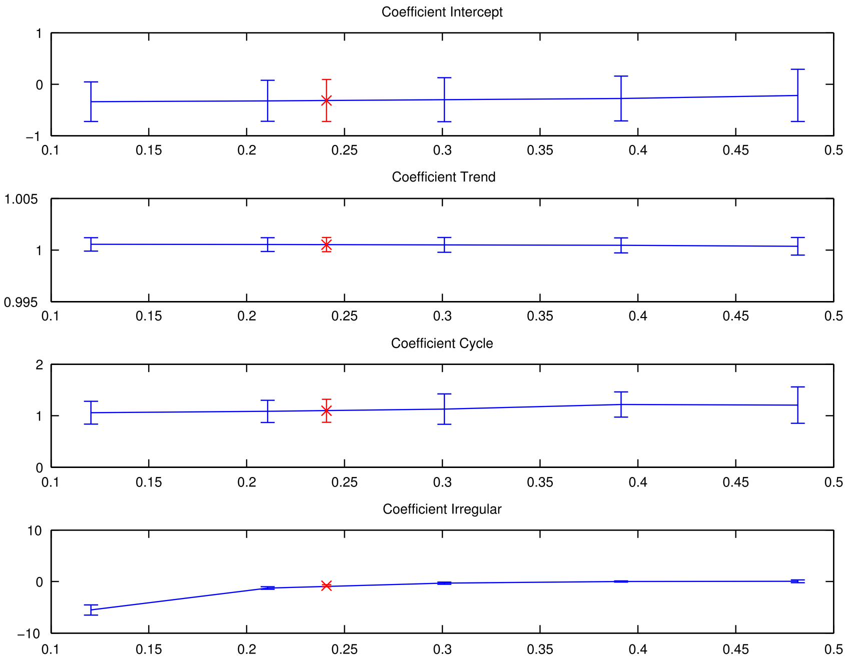

Fig. E.1. GDP deflator.

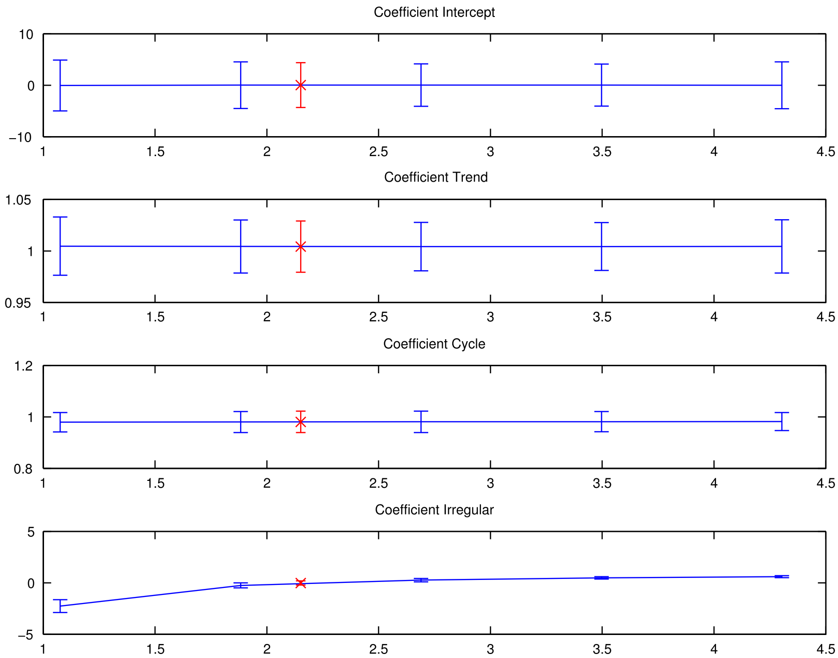

Fig. E.2. Unemployment.

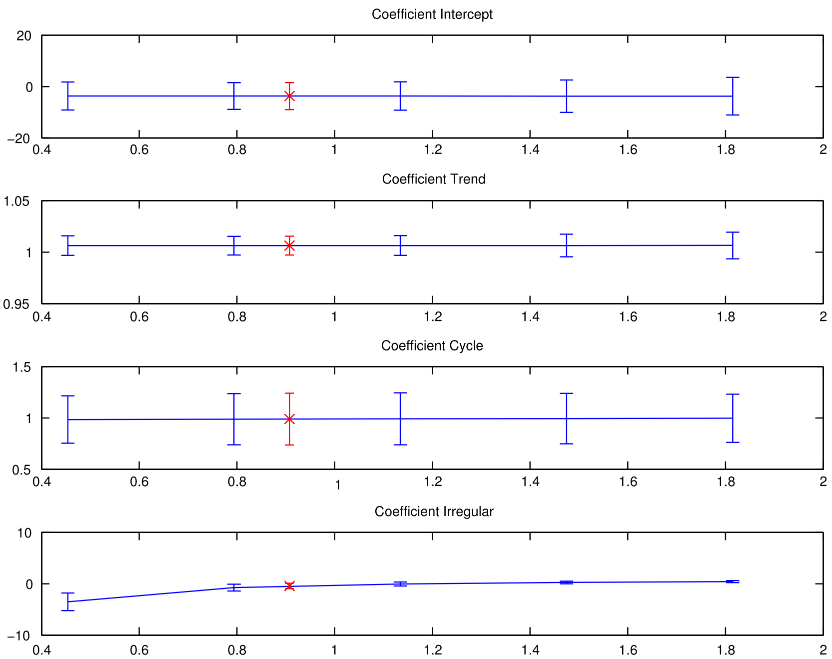

Fig. E.3. Industrial production index.

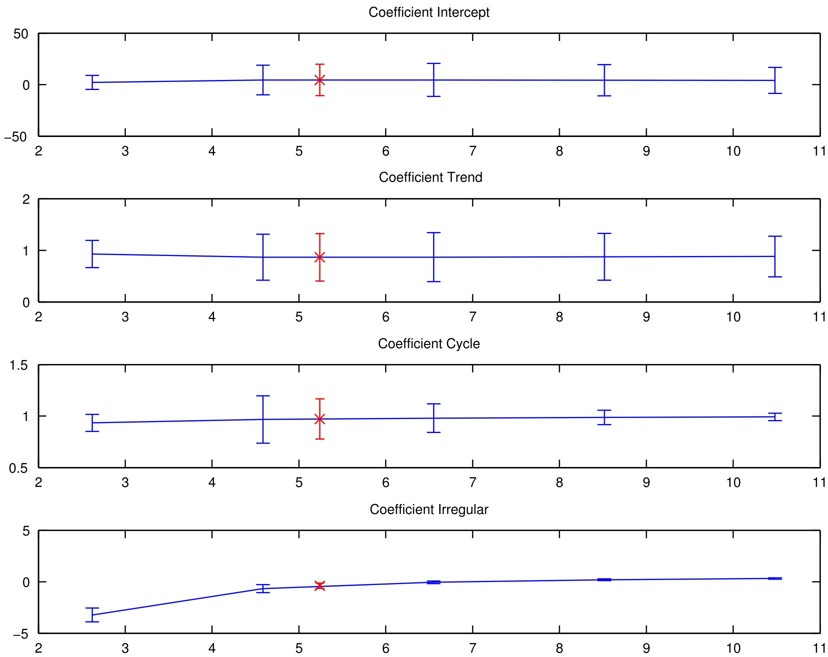

Fig. E.4. Housing starts.

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