What Do Professional Forecasters Actually Predict?*

Didier Nibbering[†] Richard Paap Michel van der Wel

Econometric Institute, Tinbergen Institute, Erasmus University Rotterdam

October 14, 2015

Abstract

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

Keywords: Forecast Evaluation, Survey of Professional Forecasters, Expert Forecast, Trend-Cycle Decomposition, State Space Modeling, Baxter-King Filter

---

*We thank Alain Hecq, Cem Çakmaklı, and Philip Hans Franses for helpful comments and suggestions. Thanks are also due to conference participants at the 20th meeting of the Netherlands Econometric Study Group (2015), the 2nd Annual Conference of the International Association for Applied Econometrics (2015), the 11th World Congress of the Econometric Society (2015), and seminar participants at the Tinbergen Institute, Erasmus University Rotterdam.

†Correspondence to: Didier Nibbering, Econometric Institute, Erasmus University Rotterdam, P.O. Box 1738, NL-3000 DR Rotterdam, The Netherlands, e-mail: nibbering@ese.eur.nl

1 Introduction

Econometric models cannot accurately predict events when developers of the models fail to include information about main drivers of the outcomes. The global financial crisis is an example of the failure of models to account for the actual evolution of the real-world economy (Colander et al., 2009). Besides econometric models also surveys of forecasters provide predictions about key economic variables. Professional forecasters may be more flexible in taking into account interpretations of economic news and various expert opinions before they form a final prediction. According to the amount of attention these surveys receive, they are perceived to contain useful information about the economy (as Ghysels and Wright (2009) note).

In this paper we examine what professional forecasters actually predict. Do they explain movements in economic time series which can also be explained by regular components like a trend or a business-cycle, or also an irregular component, which can hardly be predicted by econometric models and non-experts? We start decomposing historical time series corresponding to forecasts of six key economic variables (GDP, the GDP price index, corporate profits, unemployment, industrial production and housing starts) of the US economy in three components. Subsequently we examine whether panelists of the Survey of Professional Forecasters can explain the variation in the time series due to the different estimated components.

To decompose the economic variables we apply two commonly used methods in the literature to extract trends and business-cycles from time series. First we apply the Baxter and King (1999) low-pass filter which Baxter (1994) uses for the decomposition of exchange rates series into a trend, business-cycle, and irregular component. Second, we perform the same decomposition through a state space model which is studied by Harvey (1985). Next, we regress the forecasts of the professional forecasters on 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). To account for two-step uncertainty in the standard errors we implement the Murphy and Topel (2002) procedure.

Our results show that the professional forecasters can predict almost all variation in the time series due to the trend and the business-cycle components, but explain little or even nothing of the variation in the irregular component. Both approaches to time series decomposition lead to approximately the same results in the forecast regressions. A structural time series model, which is commonly used to estimate trends and cycles in time series, can produce almost the same predictions as the Survey of Professional Forecasters.

Although forecast performance is a widely debated topic, we are, to the best of our knowledge, the first to assess forecasts from the perspective of 'what' is predicted instead of 'how good' the actual values are predicted. Hyndman and Koehler (2006) state that "despite two decades of papers on measures of forecast error" the recommend measures still have some fundamental problems. Moreover, all these measures are relative and have to be compared to a benchmark model. By assessing whether a significant amount of variation of 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 determines why firms spends millions of dollars to purchase professional forecasts. These firms may believe that experts have information about irregular movements in the future which cannot be predicted by econometric models.

The performance of professional forecasts have been subject to a number of studies. Thomas et al. (1999); Mehra (2002); Gil-Alana et al. (2012) show that forecast surveys outperform benchmark models for forecasting inflation. These papers focus on the relative strength of expert forecasts in comparison to other forecast methods. In a comprehensive study, Ang et al. (2007) also show that professional forecasters outperform other forecasting methods in predicting inflation by means of relative measures and combinations of forecast methods. 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 et al. (2011) examine forecasts of various Dutch macroeconomic variables and conclude that expert forecasts are more accurate than model-based forecasts. Other papers show limited added value of professionals' forecasts. Franses and Legerstee (2010) show that in general experts are worse than econometric models in forecasting SKU-level sales. Isiklar et al. (2006) find that professional forecasts of Consensus Economics do not include all available new information. Billio et al. (2013)

show that the performance trade-off between a white noise model and professional forecasts in predicting returns differs over time.

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, on which we apply the methods. Section 4 discusses the results obtained from the time series decompositions and the forecast regressions and Section 5 checks the robustness of these results. We conclude with a discussion in Section 6.

2 Methods

To examine what professional forecasters actually forecast, we decompose the historical values for the predicted time series into three components; a trend, business-cycle, and irregular component. Since the Survey of Professional Forecasters only provides seasonally adjusted data, we consider seasonally adjusted time series and hence do not model the seasonal component. 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 each method relies on different assumptions we perform both methods and assess whether the results correspond with each other. In Section 2.1, we discuss 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. Moreover, it explains how we can use the state space model to produce simple model-based forecasts. Finally, Section 2.3 assesses which components are predicted by the professional forecasters by regressing their forecasts on both the estimated components in the spectral analysis and on 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, 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 by a 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 weights $a_k = a_{-k}$ specified as

$$b_0 = \omega/\pi, \tag{3}$$

$$b_k = \sin(k\omega)/(k\omega), \quad k = 1, ..., K, \tag{4}$$

$$a_k = b_k + \theta, \tag{5}$$

where

$$\theta = (1 - \sum_{k=-K}^{K} b_k)/(2K+1) \tag{6}$$

is the normalizing constant which ensures that the low-pass filter places unit weight at the zero frequency. We denote the low-pass filter by $LP_K(p)$ where K is the lag parameter for which $K = 12$ is assessed as appropriate for quarterly data by Baxter and King (1999). 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 and the end of the sample period. The periodicity of cycles is a function of the frequency ω: $p = 2\pi/\omega$. We follow Baxter and King (1999) in the definition of the business-cycle as cyclical components of no less than six quarters and fewer than 32 quarters in duration, and assign all components at lower frequency to the trend and higher frequencies to the irregular component. Thus, the filtered trend equals $LP_{12}(32)$ and the filtered business-cycle $LP_{12}(6) - LP_{12}(32)$. The filtered irregular component equals the original time series y_t minus the filtered trend and filtered business-cycle component.

2.2 State Space Model

Although the Baxter and King filter is a simple and effective methodology in extracting trends and cycles from time series, it does not allow for making 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 arbitrarily choosing the frequency bands. However, estimation of the model parameters must be feasible, and also in the time domain we have to make assumptions on the functional form of the model.

A commonly used 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 representing the business-cycle, we consider the following model;

$$y_t = \mu_t + c_t + \varepsilon_t, \qquad \varepsilon_t \sim N(0, \sigma_\varepsilon^2), \tag{7}$$

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

$$\mu_{t+1} = \mu_t + \nu_t + \xi_t, \qquad \xi_t \sim N(0, \sigma_\xi^2), \tag{8}$$

$$\nu_{t+1} = \nu_t + \zeta_t, \qquad \zeta_t \sim N(0, \sigma_\zeta^2), \tag{9}$$

where ν_t represents the slope of the trend. We opt for a smooth trend specification by restricting σ_ξ^2 to zero. The business-cycle component is represented by the following relations

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

$$c_{t+1}^* = -\rho c_t \sin\lambda + \rho c_t^* \cos\lambda + \kappa_t^*, \qquad \kappa_t^* \sim N(0, \sigma_\kappa^2), \tag{11}$$

where the unknown coefficients ρ, λ, and σ^2_κ 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 $0 < \lambda < \pi$.

We estimate the unknown parameters $\theta = (\sigma^2_\varepsilon, \sigma^2_\xi, \sigma^2_\zeta, \sigma^2_\kappa, \rho, \lambda)$ in a state space framework;

$$y_t = Z\alpha_t + \varepsilon_t, \qquad \varepsilon_t \sim N(0, \sigma^2_\varepsilon), \tag{12}$$

$$\alpha_{t+1} = T\alpha_t + \eta_t, \qquad \eta_t \sim N(0, Q), \tag{13}$$

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 modelled in the state equation. We use Kalman filtering and smoothing to obtain maximum likelihood parameter estimates and estimates for the state vector components (Durbin and Koopman, 2012).

Where the objective of the estimation routine is to minimize the observation noise ε_t relative to the trend and the cycle, we are in this case also interested in the irregular component. So instead of allocating all variance in the time series to the trend and cycle components, the observation noise has to capture the irregular movement. To prevent the variance of the observation noise (σ^2_ε) from going to zero, we fix it to the value of the variance of the estimated irregular component in the low-pass filter. As we show in Section 4.2, results are robust with respect to alternative values for the variance of the observation noise.

Besides the fact that the state space framework enables statistical inference, we can also use the model to produce forecasts by ourselves. We construct forecasts of the state space model using the Kalman filter in the following manner: First, we split the sample in an estimation and an evaluation period. Second, we forecast the values of the time series in the evaluation period by one-step-ahead forecasts. We estimate the state space model parameters on all data available up to and including time period t when we forecast the value for time period $t + 1$, which mirrors the timing of professional forecasters. This means that we extend our estimation window with one period each time we predict the next period.

2.3 Forecast Regression

Both the spectral analysis and the state space model yield a decomposition 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 by the regression equation

$$f_t = \beta_0 + \beta_1 \hat{\mu}_t + \beta_2 \hat{c}_t + \beta_3 \hat{\varepsilon}_t + v_t, \tag{14}$$

where f_t is the professional forecast, $\hat{\mu}_t$ represents the estimated trend, $\hat{c}_t$ the estimated business-cycle, and $\hat{\varepsilon}_t$ the estimated irregular component. When the professional forecasters perfectly predict the actual values, 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 case the coefficients of the estimated components equal one.

Since many economic time series exhibit trending behaviour, we expect a stochastic trend in the series of professional forecasts. The same holds for the estimated trend component, where we explicitly modeled a unit root in the local linear trend model in the state space framework. However, unless professional forecasters have done a very poor job, there is a long-run relationship between the stochastic trend of the economic time series and the predicted values for this variable. So, we expect that the forecasts and the estimated trend are cointegrated. To examine this conjecture, we test in our empirical analysis for cointegration between the professional forecasts and the estimated trend with the Engle-Granger residual-based cointegration test (Engle and Granger, 1987).

In case of cointegration, we have in (14) a regression with cointegrated variables f and $\hat{\mu}$ together with the $I(0)$ variables $\hat{c}$ and $\hat{\varepsilon}$. Park and Phillips (1989) show that in this situation the parameters can be consistently estimated with ordinary least squares. They also provide asymptotically chi-squared distributed Wald test statistics for inference on the estimated parameters (Park and 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 (14) 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. Therefore 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 we 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 with the state space model parameter covariance matrix results in asymptotically correct standard errors.

It might be appealing to simultaneously estimate the historical time series components using (7)–(11) and the forecast regression coefficients in (14) by including the forecast regression in the state space framework. In this way we directly estimate standard errors for the estimated forecast regression coefficients, without the concern that we ignore 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. For this reason we do not consider this simultaneous set-up.

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 which are available over a long time. We consider nominal GDP, GDP price index, nominal corporate profits after tax, unemployment, industrial production index, and housing starts. The forecasts for the Survey of Professional Forecasters are provided by the Federal Reserve Bank of Philadelphia.

To determine the information sets of the forecasters at the moment of providing the forecasts, we consider the timing of the survey. The quarterly survey, formerly conducted 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. Table 1 shows all relevant information concerning the timing of the survey since it is conducted by the Philadelphia Fed. There is 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 suppose that all panelists in the survey are informed about the

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

Survey	Questionnaires Sent	Last Quarter in Panelists' Information Sets	Deadline 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

The first three columns of this table provide the dates 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 set 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.

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.

Since the individual forecasters in the survey have limited histories of responses and forecasters may switch identification numbers, we 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 in each time period. Table 2 lists the series, which are all seasonally adjusted. The base year for the GDP price index and the index of industrial production changed several times in the considered sample period. We rescale the actual historical time series and the forecasts to base year 1958 in case of the GDP price index and 1957-1959 in case of the index of industrial production. All base year changes and a detailed explanation of the Survey of Professional Forecasters can be found in the documentation of the Federal Reserve Bank of Philadelphia.[1]

In this paper we consider the logarithm of all historical time series and forecasts multiplied by one hundred. Figure 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

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

Table 2: Variables Description

Variable	Description
NGDP	Annual rate nominal GDP in billion dollars.
	Prior to 1992 nominal GNP.
PGDP	GDP price index with varying base years.
	Prior to 1996 GDP implicit deflator and prior to 1992 GNP deflator.
CPROF	Annual rate nominal corporate profits after tax in billion dollars.
	Prior to 2006 excluding IVA and CCAdj.
UNEMP	Unemployment rate in percentage points.
INDPROD	Index of industrial production with varying base years.
HOUSING	Annual rate housing starts in millions.

This table provides a short summary of each variable. All variables are seasonally adjusted.

Table 3: Forecast Bias Estimates

	NGDP	PGDP	CPROF	UNEMP	INDPROD	HOUSING
Bias	-0.165	-0.012	-0.742	0.800	-0.039	-0.391
St. dev.	0.750	0.446	5.998	2.438	1.284	7.085

This table shows the forecast bias and the standard deviation for each variable. The bias is computed as the average over the difference between the predictions of the Survey of Professional Forecasters and the actual historical values. A positive bias means that the forecasters on average overestimate the actual values.

of Professional Forecasters. We recognize an upward trend in nominal GDP, GDP price index, nominal corporate profits, and industrial production index. The latter two also show some cyclical movements. From unemployment and housing we cannot directly identify a trend, but we see clear cyclical patterns in these series.

Table 3 shows the forecast bias for each variable computed as the average over the difference between the predictions of the survey of professional forecasters and the actual historical values. A positive bias means that the professional forecasters on average overestimate the actual values. Except for unemployment all series are on average underestimated. In general, the forecast bias is close to zero.

4 Results

In this section we discuss the results of the 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 analysis. Second, we examine the relation between the professional forecasts and the estimated components. Finally, we compare the professional forecasts to the structural time series model predictions.

4.1 Time Series Decomposition

Figure 2 shows nominal GDP decomposed in a trend, a cycle, and an irregular component by the low-pass filters and the state space model. For all components the two time series follow roughly the same pattern. Because the two methods rely on different assumptions, this is not trivial. The fact that the methods result in approximately the same decomposition, indicates that the estimated decompositions are reliable. We conclude the same for the other time series, that is GDP price index, nominal corporate profits after tax, unemployment, industrial production index, and housing starts, for which the figures can be found in Appendix A.

Table 4 shows the state space model parameter estimates. Almost all parameter estimates are significant. The estimated period of the cycle in GDP equals nineteen quarters, which lies in the business-cycle period interval defined by Baxter and King. Except for the corporate profits (52 quarters) and housing starts (33 quarters), this is also the case for all other variables.

4.2 Forecast Regression

As discussed in Section 2.3, for correct inference of the forecast regression parameters in (14) the forecasts should be cointegrated with the estimated trend. Table 5 shows the Engle-Granger cointegration test results on both the estimated trend in the spectral analysis as the estimated trend in the state space model. The null hypothesis of no cointegration is rejected at a 5% significance level in all cases, except for the trend in the GDP price index resulting from the spectral analysis. Hence, we have to be more careful interpreting the results of the forecast regression

Table 4: State Space Model Parameter Estimates

	Estimate (Std. error)					Implied
	σ_ε	σ_ζ	σ_κ	λ	ρ	Cycle
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)	
CPROF	3.722	0.061	5.461	0.121	0.956	52
		(0.042)	(0.435)	(0.028)	(0.018)	
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)	

This 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. The 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), implied by the λ estimate.

for this variable. For the other five variables we can straightforwardly use the Park and Phillips (1989) test statistics.

We include the estimated components in the forecast regression equation (14) to examine how the professional 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 after twelve quarters from 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 estimated series in the state space framework, which

Table 5: Cointegration Tests 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
CPROF	-5.606	1	0.000	-4.641	1	0.001
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 forecast time series is the dependent variable and an intercept is included. The 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.

results in a sample period from the last quarter of 1971 to the second quarter of 2011.

Tables 6 and 7 show the estimated coefficients for each component 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 critical value 3.842 at the 5% significance level. The asterisks indicate whether a coefficient significantly differs from the value that is expected in a perfect forecast. The first six columns of each table show the forecast regression for each variable with intercept, and the last four columns the results without intercept ($\beta_0 = 0$). Moreover, for both regressions the Wald statistic is reported together with the p-value on the null hypothesis that the coefficients are jointly equal to the weights in the perfect forecast.

The first six columns of Table 6 show that the trend and cycle components

Table 6: Forecast Regressions Based On Spectral Analysis

	Estimate (Std. error)				Wald	Estimate (Std. error)			Wald
	intercept	trend	cycle	irreg.	test	trend	cycle	irreg.	test
NGDP	−1.178	1.001	0.954	0.249*	34.897	1.000*	0.959	0.248*	30.829
	(0.620)	(0.001)	(0.037)	(0.149)	0.000	(0.000)	(0.038)	(0.154)	0.000
	3.613	2.752	1.505	25.494		10.051	1.150	23.802	
PGDP	−0.197	1.000	0.990	−0.132*	43.620	1.000	0.992	−0.133*	42.641
	(0.505)	(0.001)	(0.037)	(0.173)	0.000	(0.000)	(0.039)	(0.174)	0.000
	0.153	0.120	0.080	42.95		0.839	0.045	42.302	
CPROF	−1.552	1.001	0.849*	0.102*	50.164	0.999	0.849*	0.102*	49.662
	(2.548)	(0.005)	(0.041)	(0.155)	0.000	(0.001)	(0.041)	(0.157)	0.000
	0.371	0.106	13.475	33.329		3.404	13.242	32.944	
UNEMP	1.318	0.997	0.949*	0.581*	44.220	1.004*	0.945*	0.587*	42.194
	(1.960)	(0.011)	(0.016)	(0.104)	0.000	(0.001)	(0.015)	(0.102)	0.000
	0.452	0.067	9.966	16.208		18.975	13.982	16.418	
INDPROD	−3.491	1.006	0.938*	0.441*	18.540	1.000	0.939*	0.440*	12.638
	(1.936)	(0.003)	(0.030)	(0.168)	0.000	(0.000)	(0.030)	(0.166)	0.005
	3.251	3.194	4.386	11.122		0.102	4.246	11.401	
HOUSING	2.555*	0.919*	0.888*	0.239*	83.413	0.973*	0.847*	0.252*	77.739
	(0.880)	(0.022)	(0.038)	(0.119)	0.000	(0.010)	(0.036)	(0.119)	0.000
	8.423	13.960	8.832	40.781		6.847	18.427	39.817	

This table shows the parameter estimates in forecast regression (14) of the professional forecasts on the low-pass filter decomposition, with and without 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. An asterisk ($*$) denotes that the coefficient significantly differs from the weight expected in a perfect forecast at the 5% significance level. The reported Wald test statistic (together with the p-value) tests whether the coefficients jointly differ from the weights expected in a perfect forecast.

receive a weight close to one. Although some of these estimates significantly differ from one due to the small standard errors, we can say that the professional forecasters can predict most of the variation caused by a trend and a business-cycle. However, the parameter estimates corresponding to the irregular component differ significantly from one while having large standard errors. Moreover, about 50% of the weights of the irregular components do not significantly differ from zero, which means that the professional forecasters only capture little of the irregular movements in the time series.

When the weights of the estimated components equal one, the estimated intercept accounts for a potential bias in the level of the forecasts. Because most variables are on average underestimated by the professional forecasters, we estimate in most cases a negative intercept. 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 for the irregular component are similar as before (last four columns of Table 6). Moreover, unreported results show that fixing the coefficients of the trend and cycle components to one, barely changes the results with respect to the estimated weights of the irregular components.

We conduct a Wald test to assess whether the professional forecasts differ significantly from the perfect forecast, that is the bias, trend, cycle, and irregular component get weight of $(0, 1, 1, 1)$, respectively. The Wald tests provide p-values equal to 0.000 for all variables. So the professional forecasters predict significantly worse than the perfect forecast.

Table 7 shows the results based on the estimated components in the state space model. We find almost the same results. The estimated weights for the trend and cycle components are again close to one. However, it is remarkable that in case of the state space analysis all estimated weights for the irregular components are negative and in about 50% of the cases even significantly different from zero. The Wald test on the null hypothesis that the professional forecasters perfectly predict is again 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 GDP price index and housing starts.

Where we reported the White standard errors and corresponding Wald statistics in case of the components estimated in the spectral analysis in Table 6, in Table 7 ordinary standard errors and Wald statistics are reported. These standard errors do not take into account 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 in the state space model on the results of the forecast regression by reporting the two-step standard errors and corresponding Wald statistics.

The second column of Table 8 shows that the standard errors of the intercepts are now even larger. However, the forecast bias for nominal GDP, industrial production index, and housing starts is still significantly different from zero. Where the weights for the trend and cycle components of housing starts significantly differ from one in case of ordinary standard errors, they do not significantly differ from

Table 7: Forecast Regressions Based On State Space Model

	Estimate (Std. error)				Wald	Estimate (Std. error)			Wald
	intercept	trend	cycle	irreg.	test	trend	cycle	irreg.	test
NGDP	−1.242*	1.001	1.063	−0.596*	85.013	1.000*	1.061	−0.587*	77.942
	(0.553)	(0.001)	(0.044)	(0.194)	0.000	(0.000)	(0.045)	(0.196)	0.000
	5.049	3.794	2.009	67.910		10.242	1.861	65.503	
PGDP	−0.316	1.001	1.096*	−0.804*	112.507	1.000	1.100*	−0.805*	112.080
	(0.387)	(0.001)	(0.042)	(0.171)	0.000	(0.000)	(0.042)	(0.171)	0.000
	0.666	0.627	5.242	111.429		0.100	5.757	111.773	
CPROF	−1.743	1.002	0.956	−0.621*	96.049	0.999	0.957	−0.622*	95.771
	(2.346)	(0.004)	(0.035)	(0.188)	0.000	(0.001)	(0.035)	(0.187)	0.000
	0.552	0.182	1.589	74.774		3.575	1.569	75.088	
UNEMP	0.015	1.004	0.980	−0.024*	58.129	1.004*	0.980	−0.024*	58.504
	(2.082)	(0.011)	(0.011)	(0.190)	0.000	(0.001)	(0.011)	(0.189)	0.000
	0.000	0.145	3.073	29.212		21.326	3.139	29.413	
INDPROD	−3.708*	1.006*	0.989	−0.443*	51.052	0.999	0.988	−0.436*	45.126
	(1.689)	(0.003)	(0.020)	(0.229)	0.000	(0.000)	(0.021)	(0.231)	0.000
	4.821	4.724	0.300	39.817		0.126	0.362	38.506	
HOUSING	4.520*	0.866*	0.971	−0.381*	152.197	0.975*	0.939*	−0.340*	128.760
	(1.240)	(0.032)	(0.020)	(0.136)	0.000	(0.011)	(0.018)	(0.141)	0.000
	13.292	17.822	2.086	103.030		5.243	10.927	90.524	

This table shows the parameter estimates in forecast regression (14) of the professional forecasts on the state space model decomposition, with and without 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. An asterisk ($*$) denotes that the coefficient significantly differs from the weight expected in a perfect forecast at the five percent significance level. The reported Wald test statistic (together with the p-value) tests whether the coefficients jointly differ from the weights expected in a perfect forecast.

one 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. It remains remarkable that all estimated weights for the irregular components are negative and that still some of these effects are significantly different from zero. The forecast regressions in the last four columns still have a few trend and cycle coefficients significantly different from one due to small standard errors, for example for nominal GDP, GDP price index, and unemployment. The Wald test statistics on the null hypothesis of perfect forecasts decrease, but all corresponding p-values are still close to zero. In general, the conclusions do not change much when we account for two-step uncertainty. The Survey of Professional Forecasters can predict almost all variation in the time series due to a trend and a business-cycle, but predict little of the variation caused by the irregular

Table 8: Forecast Regressions With Two-Step Standard Errors

	Estimate (Std. error)				Wald	Estimate (Std. error)			Wald
	intercept	trend	cycle	irreg.	test	trend	cycle	irreg.	test
NGDP	−1.242*	1.001	1.063	−0.596*	62.173	1.000*	1.061	−0.587*	56.354
	(0.553)	(0.001)	(0.046)	(0.232)	0.000	(0.000)	(0.047)	(0.233)	0.000
	5.048	3.793	1.858	47.390		10.241	1.725	46.237	
PGDP	−0.316	1.001	1.096*	−0.804*	91.449	1.000	1.100*	−0.805*	90.840
	(0.387)	(0.001)	(0.045)	(0.192)	0.000	(0.000)	(0.044)	(0.192)	0.000
	0.666	0.627	4.650	88.747		0.100	5.037	88.822	
CPROF	−1.743	1.002	0.956	−0.621*	80.888	0.999	0.957	−0.622*	80.362
	(2.447)	(0.004)	(0.067)	(0.211)	0.000	(0.001)	(0.066)	(0.211)	0.000
	0.508	0.167	0.428	58.799		3.539	0.422	59.027	
UNEMP	0.015	1.004	0.980	−0.024*	48.765	1.004*	0.980	−0.024*	49.020
	(2.098)	(0.012)	(0.012)	(0.212)	0.000	(0.001)	(0.011)	(0.211)	0.000
	0.000	0.143	2.903	23.428		21.264	2.958	23.539	
INDPROD	−3.708*	1.006*	0.989	−0.443*	39.716	1.000	0.988	−0.436*	34.378
	(1.689)	(0.003)	(0.02)	(0.261)	0.000	(0.000)	(0.021)	(0.263)	0.000
	4.818	4.722	0.298	30.571		0.126	0.359	29.823	
HOUSING	4.520*	0.866*	0.971	−0.381*	118.889	0.975	0.939	−0.340*	104.221
	(1.719)	(0.045)	(0.044)	(0.146)	0.000	(0.013)	(0.044)	(0.152)	0.000
	6.917	8.827	0.428	88.956		3.669	1.902	77.655	

This table shows the parameter estimates in forecast regression (14) of the professional forecasts on the state space model decomposition, with and without intercept. Standard errors and Wald test statistics account for 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. An asterisk ($*$) denotes that the coefficient significantly differs from the weight expected in a perfect forecast at the five percent significance level. The reported Wald test statistic (together with the p-value) tests whether the coefficients jointly differ from the weights expected in a perfect forecast.

component.

4.3 State Space Model Forecasts

Our previous results show that the professional forecasters predict little of the irregular component. To investigate this further, we compare the professional forecasts to a simple model-based prediction. We obtain these predictions from the Kalman filter in the state space model (7)–(11) in which we do not fix a signal-to-noise ratio. So the irregular component estimated by the state space model is allowed to go to zero. Together with the point-forecasts we construct confidence intervals around the predictions. The confidence interval for the Survey of Professional Forecasters is constructed by the lowest and highest individual forecast and the state space prediction comes along with a covariance matrix from which we retrieve two times the standard deviation.

Figure 3 shows the nominal GDP forecasts, the confidence intervals and the actual historical time series for the evaluation period including the last five years of the sample. The two predictions are very close to each other and follow an almost identical pattern. Where the constructed confidence interval of the professional forecasts seems narrower over the whole evaluation period, it has some outliers, while the confidence interval of the state space predictions is quite stable. Overall, the structural time series model produces almost the same predictions as the Survey of Professional Forecasters.

5 Sensitivity Analysis

In this section we perform three sensitivity analyses and illustrate the results by means of nominal GDP. First we assess the robustness of the fixed variance of the irregular component in the state space framework against a range of values. Second, instead of survey forecasts we regress model-based forecasts on the estimated components of the historical time series. Finally, we examine the limited predictive power for the irregular component in the mean of the Survey of Professional Forecasters, by decomposing these forecasts.

5.1 Fixed Variance

To estimate the components in the state space framework, the variance of the irregular component is fixed 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. Figure 4 shows the sensitivity of the estimated coefficients in the forecast regression of nominal GDP based on the estimated components in the state space model. The same figure for the other time series can be found in Appendix B.

The figure 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. The coefficient of the irregular component seems to deviate more from the weight expected in a perfect forecast when the standard deviation of the estimated irregular component decreases. So the choice to fix the variance of the irregular component is not likely to influence the results found in the forecast regressions.

5.2 Model-based Forecasts

Based on the forecast regressions we find that the mean of the Survey of Professional Forecasters only explain little of the time series variation due to the irregular component. This is surprising when we presume that professional forecasters may adapt faster and be more flexible than pure model-based prediction methods. However, we do not expect an econometric model to capture the irregular component. To test this conjecture, we regress model forecasts on the estimated components of the historical time series.

We generate forecasts with 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. Table 9 shows the forecast regression results of the one-step-ahead predictions in the sample from the first quarter of 1979 to the second quarter of 2011. The overall picture resembles the results obtained before. Both the estimated weights of the components estimated in the spectral analysis as the estimated weights of the components estimated in 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 in case one opts for a state space model approach to decompose the time series.

5.3 Forecast Decomposition

Based on the forecast regressions we find that the mean of the Survey of Professional Forecasters explain little of the variation in time series due to the irregular

Table 9: $AR(p)$ Model Forecast Regressions for Nominal GDP

	Estimate (Std. error)				Wald	Estimate (Std. error)			Wald
	intercept	trend	cycle	irreg.	test	trend	cycle	irreg.	test
Spectral	0.456	1.000	0.955	0.002	27.913	1.000	0.958	−0.002	27.823
	(1.254)	(0.001)	(0.043)	(0.224)	0.000	(0.000)	(0.044)	(0.223)	0.000
	0.132	0.061	1.122	19.872*		5.263*	0.944	20.199*	
SSM	0.818	0.999	1.079	−1.035	46.937	1.000	1.080	−1.036	46.236
	(1.032)	(0.001)	(0.063)	(0.325)	0.000	(0.000)	(0.063)	(0.325)	0.000
	0.629	0.398	1.542	39.202*		6.696*	1.604	39.323*	

This table shows the parameter estimates in forecast regression (14) of the $AR(p)$ model forecasts on the low-pass filter decomposition, with and without intercept, in the first three rows, and on the state space model (SSM) decomposition, with and without intercept, in the last three rows. In case of low-pass filter decomposition, 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. An asterisk ($*$) denotes that the coefficient significantly differs from the weight expected in a perfect forecast at the five percent significance level. The reported Wald test statistic (together with the p-value) tests whether the coefficients jointly differ from the weights expected in a perfect forecast. In case of state space model decomposition these statistics are based on the Murphy and Topel (2002) procedure.

component. To examine why the forecasters fail to predict irregular events, we apply the time series decomposition methods to the mean of the professional forecasts. Figure 5 and Figure 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 the irregular component estimated from the forecasts seem to lag behind these components 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 nominal GDP, we regress the professional forecasts on the lagged values of the components estimated from the historical time series. Table 10 shows the results. Due to small standard errors the weights of the lagged estimated trend differ significantly from one, but the weights of the business-cycle, and surprisingly, the weights of the irregular component do not significantly differ from one. This suggests that the professional forecasters explain the value of nominal GDP in the current period, which is already published, instead of explaining irregular events

Table 10: Forecast Regressions on Lagged Estimated Components

	Estimate (Std. error)				Wald	Estimate (Std. error)			Wald
	intercept	trend	cycle	irreg.	test	trend	cycle	irreg.	test
Spectral	6.610	0.994	0.989	0.951	1656.311	1.002	0.958	0.953	651.678
	(0.495)	(0.001)	(0.025)	(0.094)	0.000	(0.000)	(0.041)	(0.155)	0.000
	178.283*	110.964*	0.207	0.272		610.593*	1.081	0.092	
SSM	6.606	0.994	0.986	0.890	1753.648	1.002	0.994	0.827	580.422
	(0.419)	(0.000)	(0.034)	(0.147)	0.000	(0.000)	(0.054)	(0.236)	0.000
	248.060*	149.469*	0.169	0.560		579.675*	0.013	0.538	

This table shows the parameter estimates in forecast regression (14) of the professional forecasts on the lagged values of the low-pass filter decomposition, with and without intercept, in the first three rows, and on the lagged values of the state space model (SSM) decomposition, with and without intercept, in the last three rows. In case of low-pass filter decomposition, 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. An asterisk ($*$) denotes that the coefficient significantly differs from the weight expected in a perfect forecast at the five percent significance level. The reported Wald test statistic (together with the p-value) tests whether the coefficients jointly differ from the weights expected in a perfect forecast. In case of state space model decomposition these statistics are based on the Murphy and Topel (2002) procedure.

in the future.

6 Conclusion

In this paper we have 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. Thereafter we 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. We run these regressions based on the components estimated by the low-pass filters in the spectral analysis and the components estimated in a state space model. Both approaches lead to approximately the same results. We find that the mean of the professional forecasts can predict almost all variation in the time series due to the trend and the business-cycle but little or nothing of the variation in the irregular components. A simple state space model, which is commonly used to estimate trends and cycles in time series, can produce almost the same predictions.

The results suggest that the mean of the professional forecasts contain little information about the variation in the irregular component. Where an econometric model is by definition not capable of predicting the irregular component, one would hope that an expert does have some information about irregular movements in the future. The fact that even a simple state space model can almost replicate the predictions of the professional forecasters suggests that investors and policy makers who are still relying on professional forecasts can save a lot of money by using econometric models for forecasting economic variables. This result is not surprising when professional forecasters also use model-based techniques to construct their predictions.

Based on this research we provide some recommendations for further research. 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, cycle and irregular component. Applying the decomposition methods to unadjusted data can extend the analysis with a seasonal component. Second, we conclude that professional forecasters only predict little of the irregular component. However, this conclusion is made on the mean of the panelists' forecasts in the Survey of Professional Forecasters. Further research can perhaps investigate whether there are individual forecasters in the survey who are able to provide structural information about future irregular movements in the economy.

References

Ang, A., Bekaert, G., and Wei, M. Do macro variables, asset markets, or surveys forecast inflation better? *Journal of Monetary Economics*, 54(4):1163–1212, 2007.

Baxter, M. Real exchange rates and real interest differentials: Have we missed the business-cycle relationship? *Journal of Monetary Economics*, 33(1):5–37, 1994.

Baxter, M. and King, R. G. Measuring business cycles: Approximate band-pass filters for economic time series. *Review of Economics and Statistics*, 81(4):575–593, 1999.

Billio, M., Casarin, R., Ravazzolo, F., and Van Dijk, H. K. Time-varying combinations of predictive densities using nonlinear filtering. *Journal of Econometrics*, 177(2):213–232, 2013.

Colander, D., Goldberg, M., Haas, A., Juselius, K., Kirman, A., Lux, T., and Sloth, B. The financial crisis and the systemic failure of the economics profession. *Critical Review*, 21(2-3):249–267, 2009.

Durbin, J. and Koopman, S. J. *Time series analysis by state space methods*. Number 38. Oxford University Press, 2012.

Engle, R. F. and Granger, C. Co-integration and error correction: Representation, estimation, and testing. *Econometrica*, 55(2):251–276, 1987.

Franses, P. H. and Legerstee, R. Do experts' adjustments on model-based sku-level forecasts improve forecast quality? *Journal of Forecasting*, 29(3):331–340, 2010.

Franses, P. H., Kranendonk, H. C., and Lanser, D. One model and various experts: Evaluating dutch macroeconomic forecasts. *International Journal of Forecasting*, 27(2):482–495, 2011.

Ghysels, E. and Wright, J. H. Forecasting professional forecasters. *Journal of Business & Economic Statistics*, 27(4):504–516, 2009.

Gil-Alana, L., Moreno, A., and Pérez de Gracia, F. Exploring survey-based inflation forecasts. *Journal of Forecasting*, 31(6):524–539, 2012.

Harvey, A. C. Trends and cycles in macroeconomic time series. *Journal of Business & Economic Statistics*, 3(3):216–227, 1985.

Harvey, A. C. *Forecasting, structural time series models and the Kalman filter*. Cambridge University Press, 1990.

Hyndman, R. J. and Koehler, A. B. Another look at measures of forecast accuracy. *International Journal of Forecasting*, 22(4):679–688, 2006.

Isiklar, G., Lahiri, K., and Loungani, P. How quickly do forecasters incorporate news? evidence from cross-country surveys. *Journal of Applied Econometrics*, 21(6):703–725, 2006.

Leitch, G. and Ernesttanner, J. Professional economic forecasts: Are they worth their costs? *Journal of Forecasting*, 14(2):143–157, 1995.

MacKinnon, J. G. Numerical distribution functions for unit root and cointegration tests. *Journal of Applied Econometrics*, 11(6):601–618, 1996.

Mehra, Y. P. Survey measures of expected inflation: Revisiting the issues of predictive content and rationality. *Economic Quarterly-Federal Reserve Bank of Richmond*, 88(3):17–36, 2002.

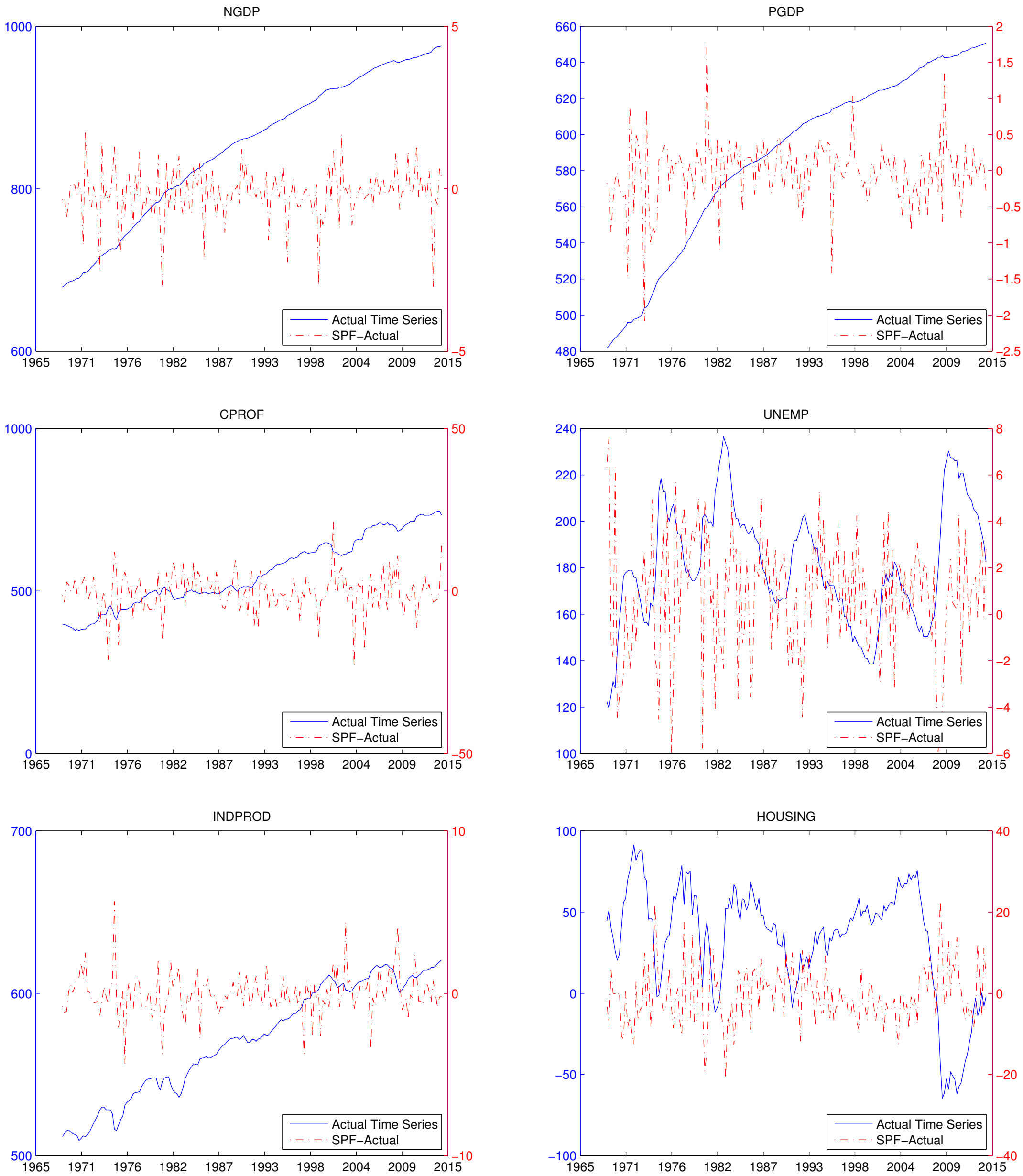
Murphy, K. M. and Topel, R. H. Estimation and inference in two-step econometric models. *Journal of Business & Economic Statistics*, 20(1):88–97, 2002.

Park, J. Y. and Phillips, P. C. Statistical inference in regressions with integrated processes: Part 2. *Econometric Theory*, 5(01):95–131, 1989.

Thomas, L. B. et al. Survey measures of expected United States inflation. *Journal of Economic Perspectives*, 13(4):125–144, 1999.

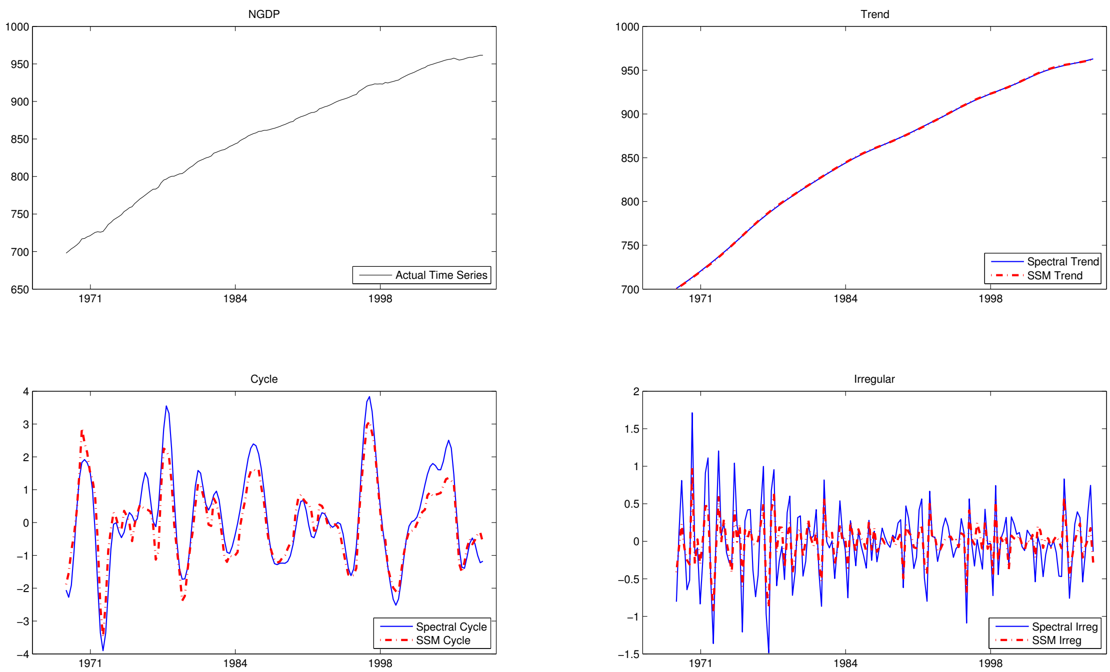
White, H. A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity. *Econometrica*, 48(4):817–838, 1980.

Figure 1: Historical Time Series and the Survey of Professional Forecasters



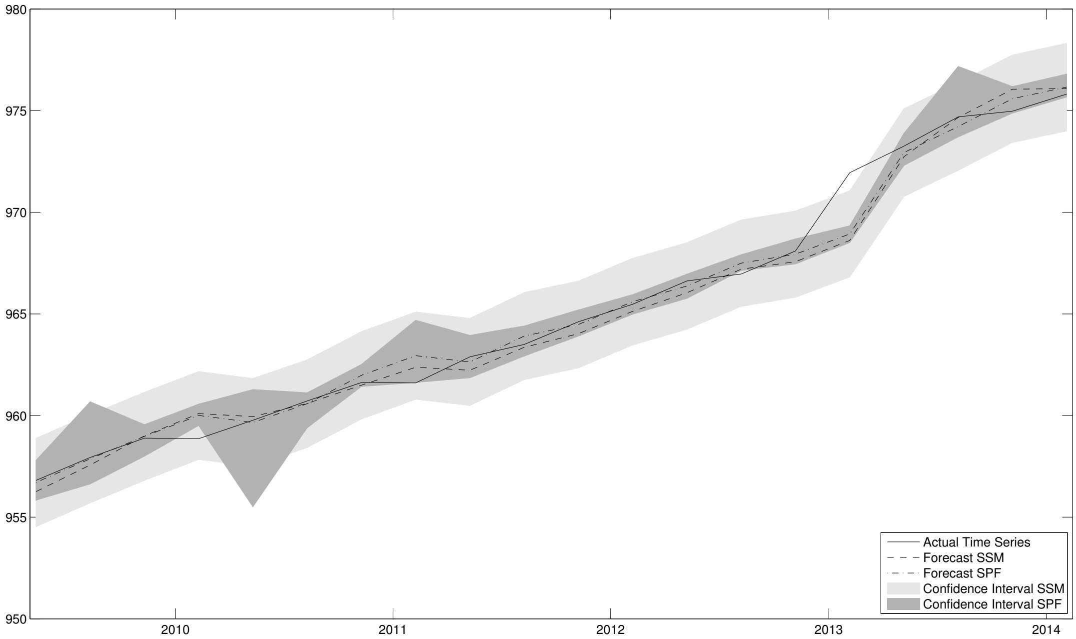
Historical time series (blue solid line, left axis) graphs together with the differences between the predictions of the Survey of Professional Forecasters and the actual values (red dashed dotted line, right axis). The figure shows the nominal GDP, GDP price index, nominal corporate profits after tax, unemployment, industrial production index, and housing starts, respectively. The time series are log transformed and multiplied by one hundred.

Figure 2: Decomposition of Nominal GDP



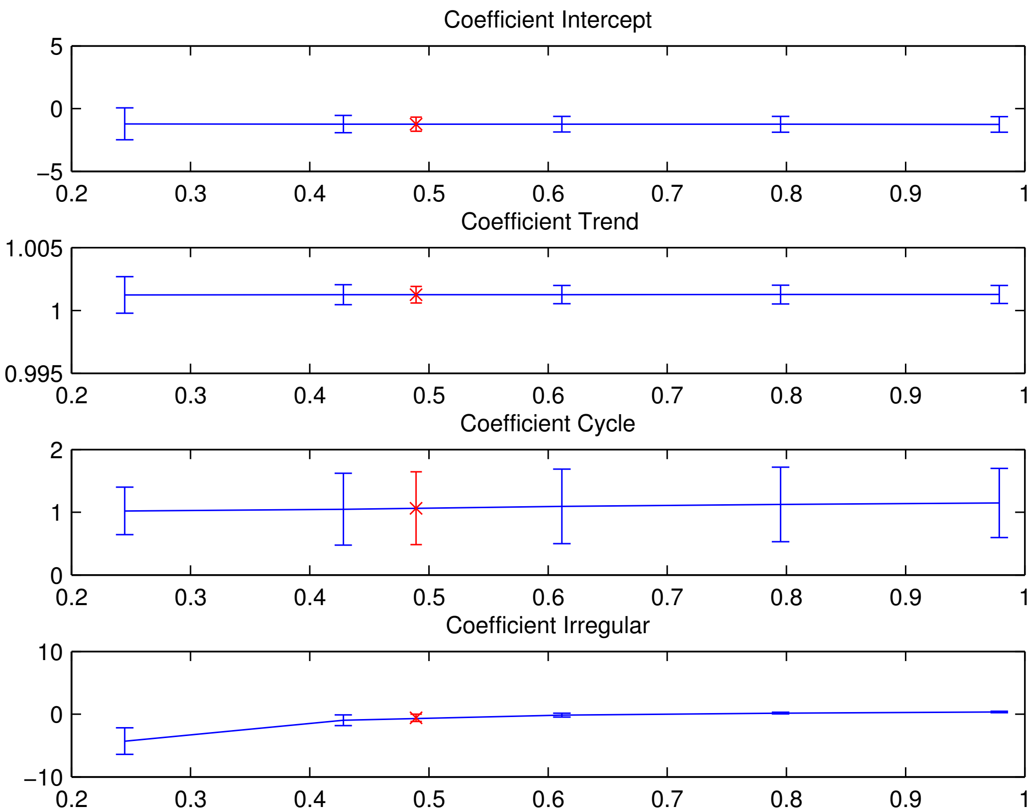
Nominal GDP decomposed in a trend, a cycle, and an irregular component by the low-pass filters and the state space model. The first window shows one hundred times the logarithm of the actual values in the historical time series and the other windows show the components estimated in the low-pass filters by a blue solid line and the components estimated in the state space model by a red dashed dotted line.

Figure 3: Model-Based and Professional Forecasts NGDP



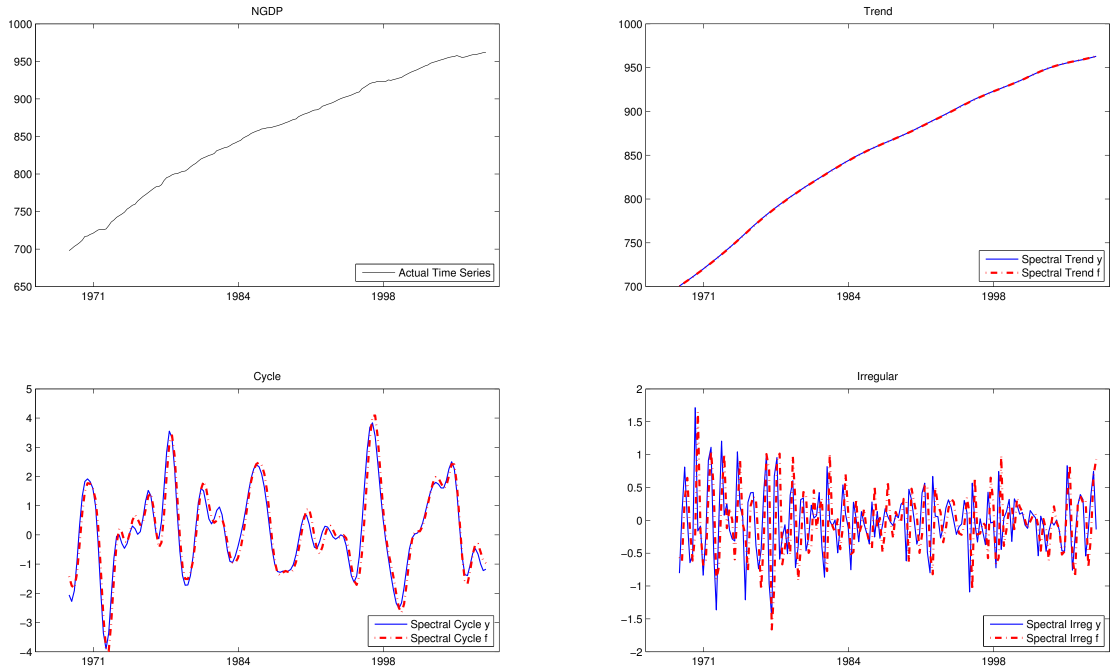
Nominal GDP predictions of the state space model (dashed line) and the Survey of Professional Forecasters (dashed dotted line) together with the actual time series (solid line). The corresponding gray surfaces represent the constructed confidence intervals of the predictions.

Figure 4: Sensitivity Analysis Fixed Variance Irregular Component



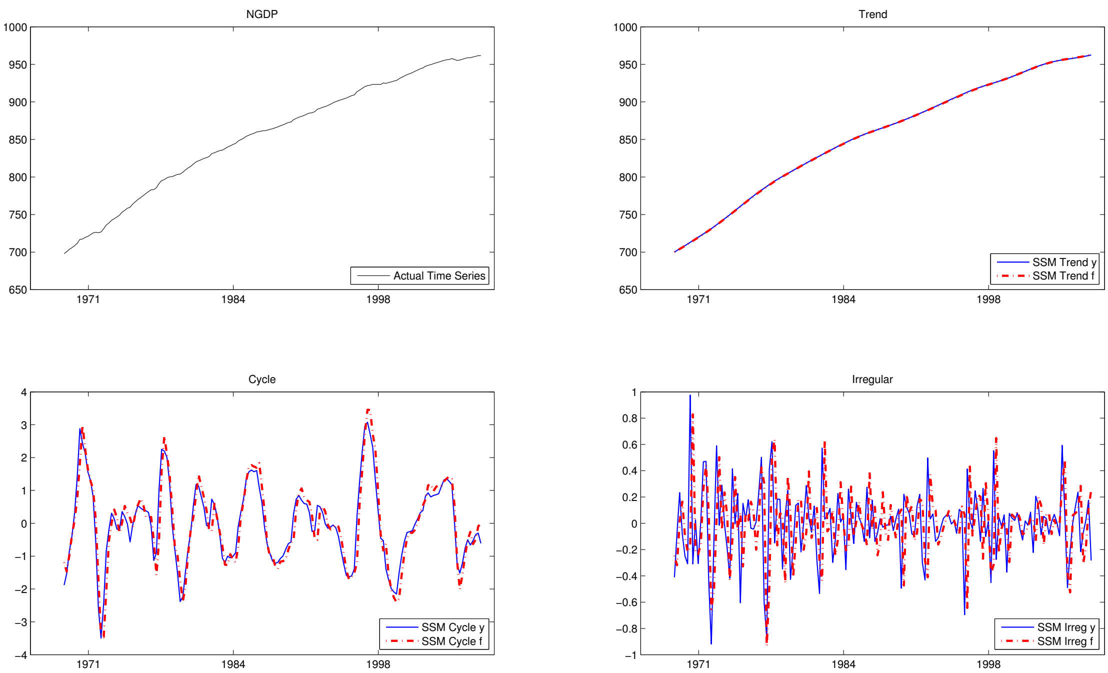
Sensitivity of the estimated coefficients in the forecast regression of nominal GDP to the standard deviation of the estimated irregular component in the state space framework. The (blue) lines show the value of the estimated coefficients with error bands of one standard error, for different values of 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.

Figure 5: Decomposition of Nominal GDP in Spectral Analysis



The historical time series and the mean of the forecasts of the Survey of Professional Forecasters for Nominal GDP decomposed in a trend, a cycle, and an irregular component by the low-pass filters. The first window shows one hundred times the logarithm of the actual values in the historical time series and the other windows 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 dashed dotted line.

Figure 6: Decomposition of Nominal GDP in State Space Model



The historical time series and the mean of the forecasts of the Survey of Professional Forecasters for Nominal GDP decomposed in a trend, a cycle, and an irregular component by the state space model. The first window shows one hundred times the logarithm of the actual values in the historical time series and the other windows 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 dashed dotted line.

A Time Series Decompositions

In Subsection 4.1 we show nominal GDP decomposed in a trend, a cycle, and an irregular component by the low-pass filters and the state space model. Here we show the decompositions of the other variables; GDP price index (PGDP), nominal corporate profits after tax (CPROF), unemployment (UNEMP), industrial production index (INDPROD), and housing starts (HOUSING). Each figure corresponding to a variable consist of four windows. The first window shows the actual values in the historical time series and the other windows 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 dashed dotted line. All variables are log transformed and multiplied by hundred.

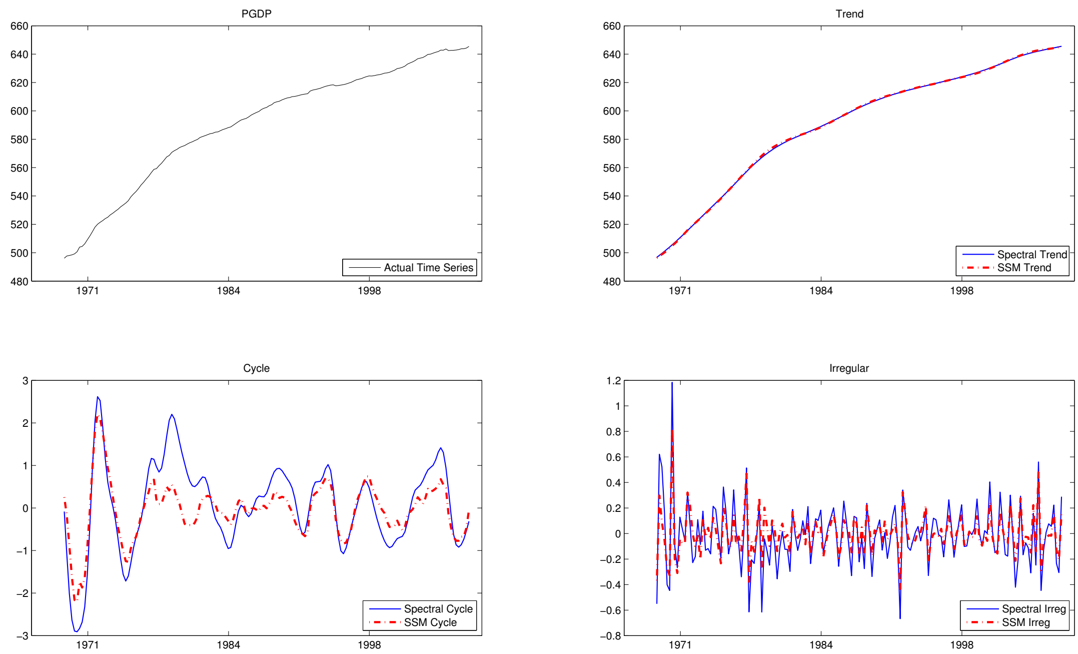


Figure A1: GDP Price Index

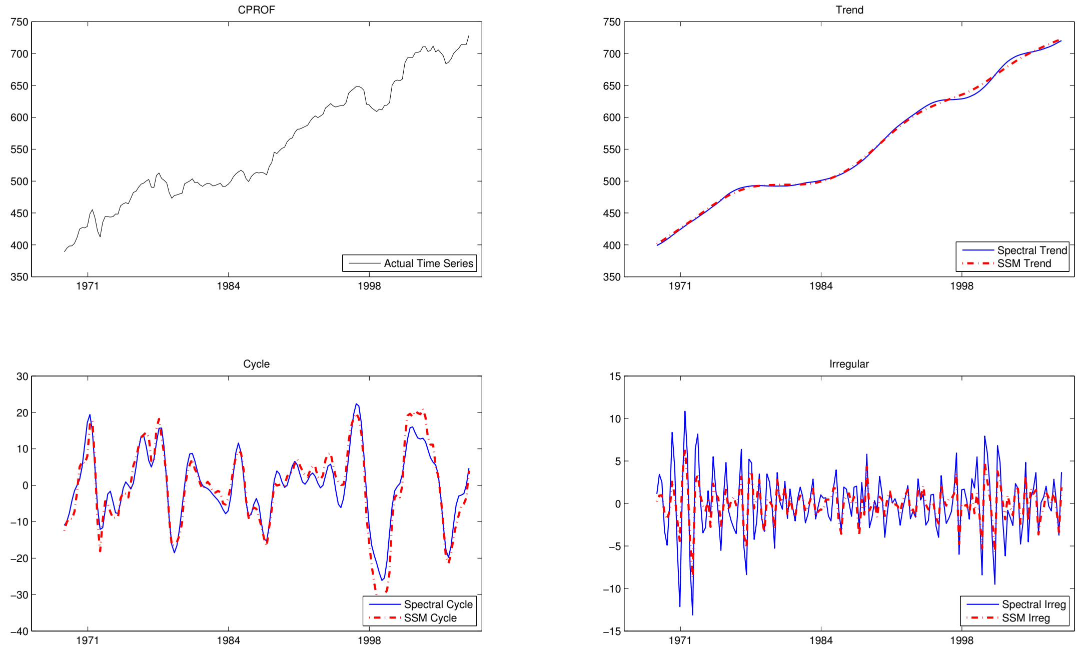


Figure A2: Nominal Corporate Profits After Tax

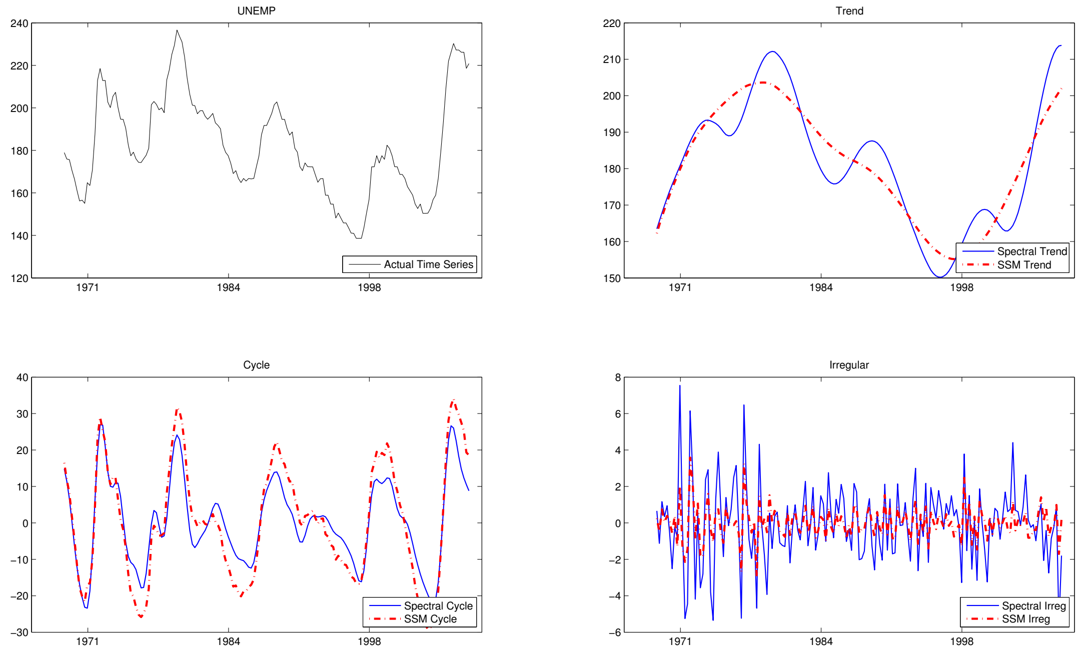


Figure A3: Unemployment

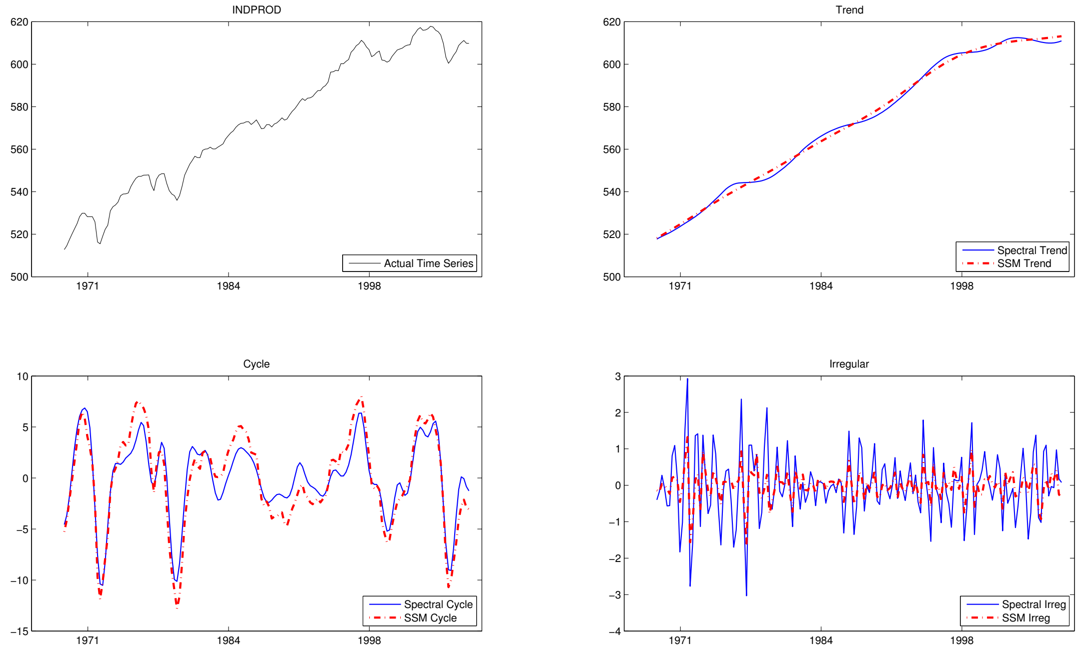


Figure A4: Industrial Production Index

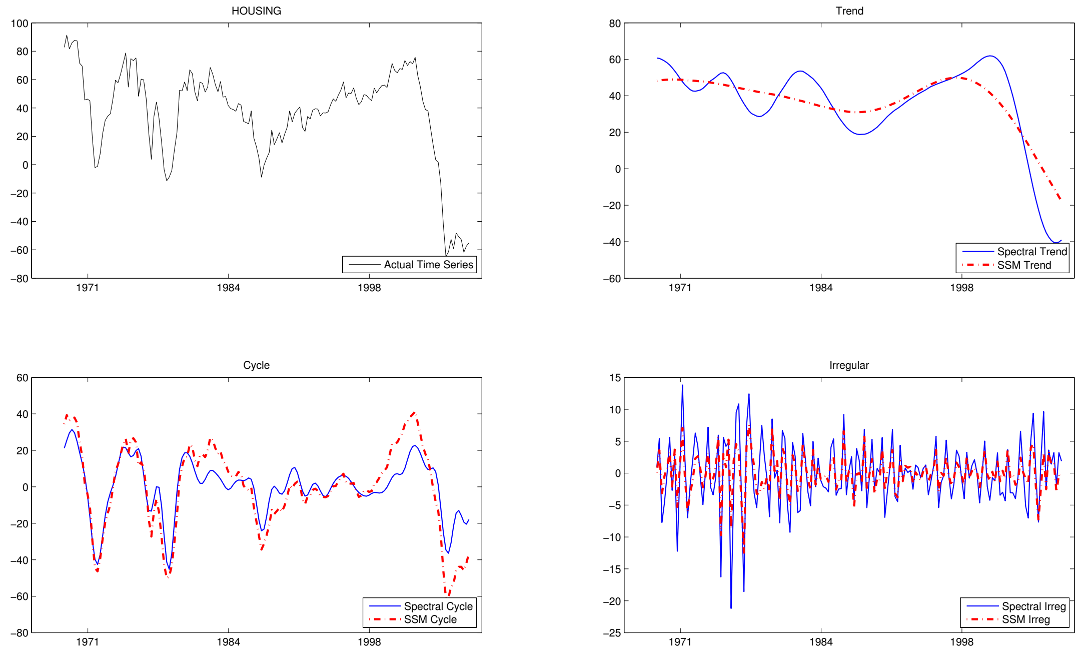


Figure A5: Housing Starts

B Sensitivity Analysis Forecast Regressions

In Subsection 4.2 we show the sensitivity of the estimated coefficients in the forecast regression of nominal GDP to the standard deviation of the variance of the estimated irregular component in the state space framework. Here we show the sensitivities of the coefficients of the components of the other variables; GDP price index (PGDP), nominal corporate profits after tax (CPROF), unemployment (UNEMP), industrial production index (INDPROD), and housing starts (HOUSING). Each figure corresponding to a variable consists of four windows; the coefficients of the intercept, trend, business-cycle, and irregular component. 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 with 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.

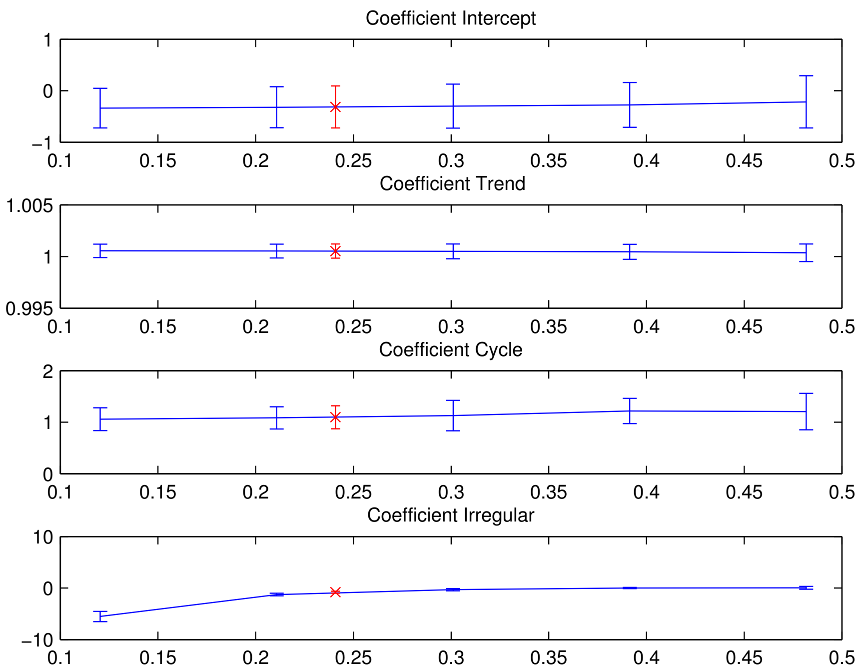


Figure B1: GDP Price Index

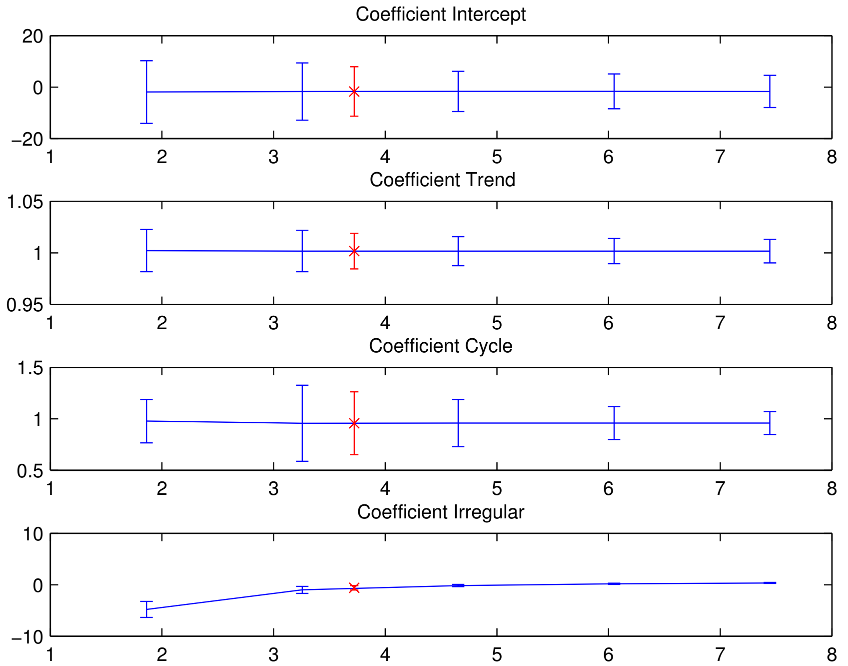


Figure B2: Nominal Corporate Profits After Tax

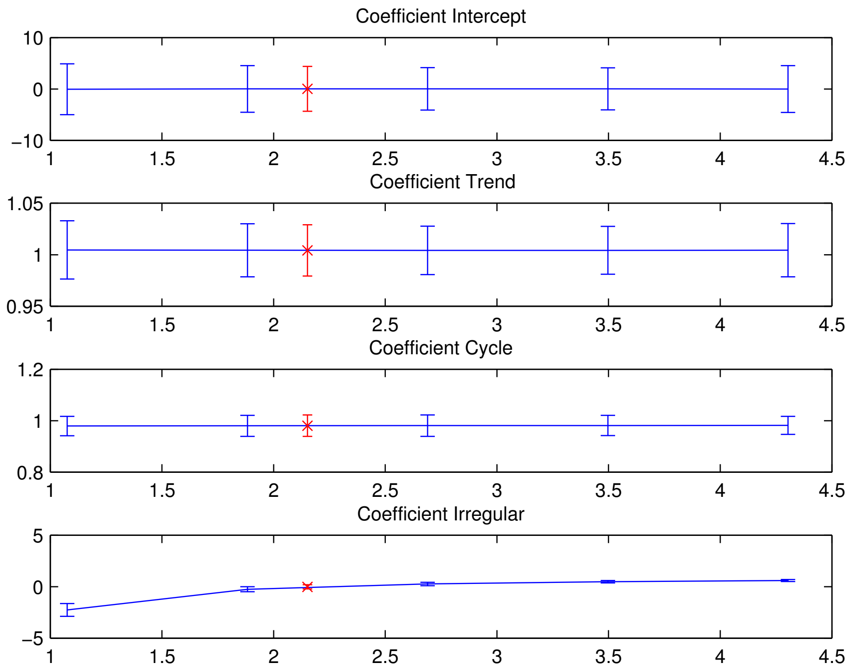


Figure B3: Unemployment

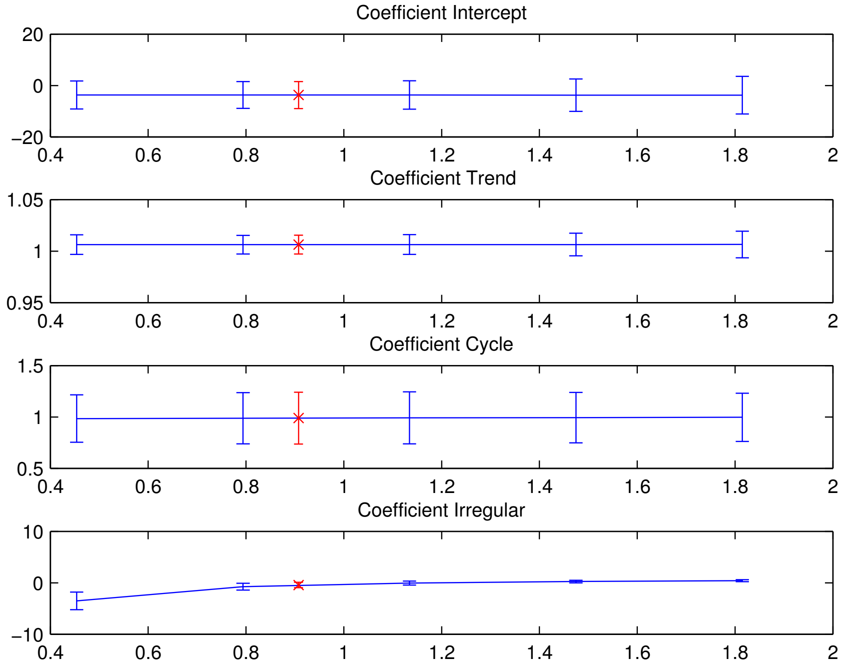


Figure B4: Industrial Production Index

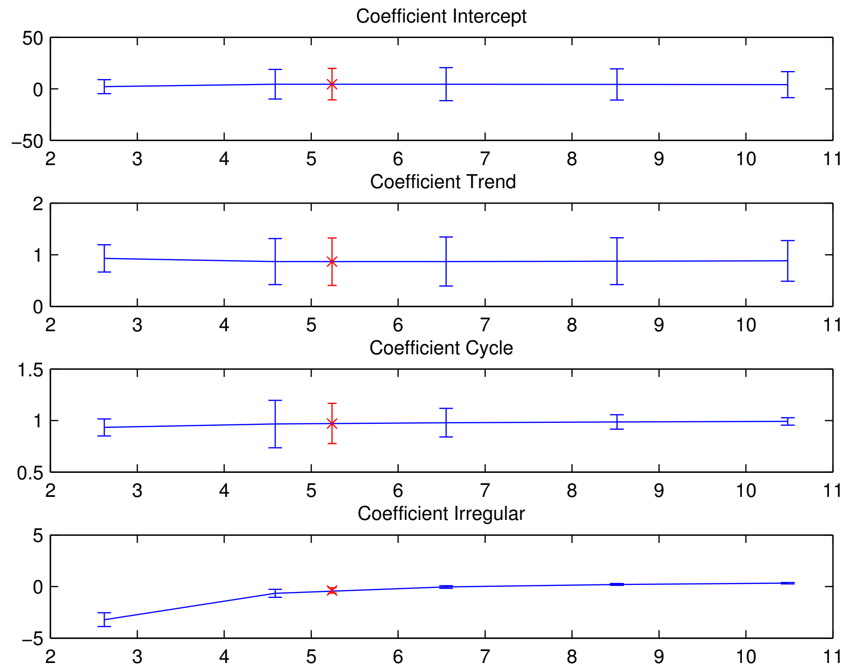


Figure B5: Housing Starts