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What do professional forecasters actually predict?

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ABSTRACT

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