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Approximating and forecasting macroeconomic signals in real-time

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ABSTRACT

We incorporate factors extracted from a large panel of macroeconomic time series in the predictions of two signals related to real economic activity: business cycle fluctuations and the medium- to long-run component of output growth. The latter is simply output growth short of fluctuations with a period below one year. For forecasting purposes, we show that targeting this object rather than the original (noisy) time series can result in gains in forecast accuracy. With conventional projections, high-frequency fluctuations are always fitted, despite being (mostly) unpredictable or idiosyncratic. We illustrate the methodology and provide forecast comparisons for the U.S. and Portugal.

1. Introduction

We present a method designed for predicting two measures of economic activity in real-time: business cycle fluctuations of aggregate output and the smooth component of output growth. Following Baxter and King (1999), business cycle fluctuations are usually defined as "fluctuations with a specified range of periodicities" in the spectrum of the time series of interest. We will pick the standard [6, 32] quarters band (see for example Stock & Watson, 1999). The smooth component of output growth (hereafter, smooth growth) is defined as output growth short of fluctuations with a period below one year. The signals just defined can be extracted through the application of well-known two-sided filters to the series of interest. Extraction in real-time is therefore restricted by the availability of data, and is thus a difficult task. Christiano and Fitzgerald (2003) and Wildi (1998) provided a univariate minimum mean squared solution to the endpoints problem, while Valle e Azevedo (2011) showed the usefulness of considering a multivariate solution.

Our main contribution is to show that it can be useful to wed multivariate filtering with factor analysis in order to improve signal extraction. We extend the analysis of Valle e Azevedo (2011), who focused solely on business cycle fluctuations, by investigating the usefulness of multivariate predictions of smooth growth as coincident/leading indicators of economic activity, and also as forecasts of the quarterly Gross Domestic Product (GDP) itself. Furthermore, we evaluate our predictions within a simulated real-time environment, in contrast to Valle e Azevedo (2011), who estimated second moments using the full sample, as opposed to using the data that were actually available at each prediction moment, for example. The resulting real activity indicators have several desirable properties: (i) they are timely, since we take into account the release delays of all of the series used in the exercise; (ii) they display few short-run oscillations, and therefore provide a clear picture of growth prospects and cyclical developments; (iii) they are based on a comprehensive panel of predictors, whose idiosyncratic components are eliminated through factor analysis; and (iv) predictions of smooth growth for period $t+h$ constructed using data available at time t forecast GDP growth itself at $t+h$ remarkably well (with h less

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than one year). We conclude that, for forecasting purposes, targeting a smooth version of a time series may be more efficient than targeting the original series. With conventional projections, short-run fluctuations are always fitted, despite being (mostly) unpredictable or idiosyncratic. At least in the context of forecasting output growth, it seems clear that a superior forecast method is not characterized by its ability to nail the high frequency fluctuations, especially at long horizons.

Our approach can be summarized as follows: we assume that the panel of predictors is described appropriately by a factor model, as was originally proposed by Geweke (1977) and Sargent and Sims (1977). We estimate the common factors using principal components, as did Stock and Watson (2002a,b).[1] Next, we use the estimated factors and the series of interest in a feasible (minimum mean squared error) projection targeting business cycle fluctuations or smooth growth. The resulting multivariate filter is an extension of the univariate filter developed by Christiano and Fitzgerald (2003) and Wildi (1998), which is itself an extension of the two-sided symmetric filter of Baxter and King (1999).[2]

Following Stock and Watson (1989), model-based (or parametric) methods assuming a factor structure have also been used to construct business cycle (or growth) indicators. Harvey and Trimbur (2003) propose unobserved components models for which the extraction of a cycle component is equivalent to applying a band-pass filter. Additionally incorporating an extension proposed by Rünstler (2004) that allows for phase shifts in the cyclical components of multiple time series, Valle e Azevedo, Koopman, and Rua (2006) construct a business cycle indicator which can be seen as a multivariate band-pass filter. In their paper, although a common factor structure is assumed to describe a small set of time series, the representation is far from general and the method does not aim to predict a pre-defined range of frequencies. That is therefore the aim of this paper. The approach closest to ours is that of Altissimo, Cristadoro, Forni, Lippi, and Veronese (2010), which resulted in the New Eurocoin indicator. The indicator is obtained by projecting the smooth component of output growth onto estimated smooth factors. We will contrast the two approaches in more detail later.

The outline of the paper is as follows. In Section 2 we define our targets precisely and describe how we predict them. In Section 3 we discuss the estimation of the factors which are used as covariates in the prediction of the signals. In Section 4 we assess the real-time performances of our predictions, analyzing results for the U.S., while in Section 5 we analyze the performances of predictions of smooth growth as forecasts of GDP growth for the U.S. and Portugal. Section 6 concludes.

[1] We could have used generalized principal components instead; see Forni, Hallin, Lippi, and Reichlin (2005) and the working paper version of this paper, Valle e Azevedo and Pereira (2008).

[2] Such solutions were provided in the case of stationary processes by Geweke (1978) and in a univariate context including unit-roots by Pierce (1980). Multivariate solutions were also analyzed by Wildi (2008) and Wildi and Sturm (2008).

2. Signals of interest and predictions

2.1. Business cycle fluctuations and smooth growth

Throughout the paper, our variable of interest will be (the log of) real quarterly GDP, as the best available proxy for aggregate economic activity. Define x_t as the log of real GDP and $\Delta x_t = (1 - L)x_t$ as its growth rate, where L is the lag operator. We define business cycle fluctuations as fluctuations in x_t with periods in the range [6, 32] quarters. Smooth growth is defined as GDP growth short of fluctuations with a period below one year (or 4 quarters). Specifically, take the following decompositions of x_t and Δx_t:

$$x_t = \mathrm{BC}(L)x_t + (1 - \mathrm{BC}(L))x_t \tag{1}$$

$$\Delta x_t = \mathrm{SG}(L)\Delta x_t + (1 - \mathrm{SG}(L))\Delta x_t, \tag{2}$$

where $\mathrm{BC}(L) = \sum_{j=-\infty}^{\infty} BC_j L^j$ and $\mathrm{SG}(L) = \sum_{j=-\infty}^{\infty} SG_j L^j$ are the "ideal" filters isolating the [6, 32] and [4, ∞[quarters bands, respectively. The filter weights, BC_j and SG_j, are well-known, see for example Altissimo et al. (2010) and Baxter and King (1999). Business cycle fluctuations are defined as $\mathrm{BC}(L)x_t$, and smooth growth is defined as $\mathrm{SG}(L)\Delta x_t$. Business cycle fluctuations can reasonably be interpreted as those fluctuations in real GDP which are not attributable to either long-run growth or high-frequency measurement error. Smooth growth is a measure of output growth which is free of the short-run oscillations that make the assessment of the current aggregate economic situation difficult. We believe that this is an extremely useful measure, especially for (small) economies in which GDP data are prone to exhibiting noisy behaviors, reflecting unrepeatable events or a mismatch between the concept of output and its measurement (as is quite evident in the case of Portugal).[3]

Obviously, it is not possible to extract these signals with an arbitrary precision in finite samples, let alone in a real-time context. However, accurate predictions can be obtained in the middle of the sample. For instance, the filter developed by Baxter and King (1999) (BK filter), which amounts to truncating the ideal filter at a specified lead/lag, provides very accurate predictions of the signals if the truncation lead/lag is sufficiently large. Fig. 1 presents two (approximate) decompositions of x_t and Δx_t for the U.S. obtained with the BK filter. Given the fixity of the lag orders and of the filter weights, these predictions do not suffer from revisions once more GDP data become available. Furthermore, the consideration of additional leads and lags of GDP data would lead to negligible differences between these predictions and those obtained with the "ideal filters" $\mathrm{BC}(L)$ and $\mathrm{SG}(L)$, while implying the loss of even more filtered observations near the endpoints of the sample. Notice, however, that we are particularly interested in obtaining predictions of these signals for the current quarter (coincident indicator), the next quarter (leading indicator), or any other future quarter.

[3] Several examples can be given: for instance, a (large) purchase of aircraft by an airline can be registered (in national accounts) as investment in a given quarter and as imports next quarter. This creates (as it has done in the past) a peak in measured GDP growth, followed by a trough.