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Monitoring the world business cycle☆

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ABSTRACT

We propose a Markov-switching dynamic factor model to construct an index of global business cycle conditions, to perform short-term forecasts of world GDP quarterly growth in real time and to compute real-time business cycle probabilities. To overcome the real-time forecasting challenges, the model accounts for mixed frequencies, for asynchronous data publication and for leading indicators. Our pseudo real-time results show that this approach provides reliable and timely inferences of the world quarterly growth and of the world state of the business cycle on a monthly basis.

1. Introduction

The drastic downturn in the global economy in 2009 led the economic agents to acknowledge the need for new tools to monitor the ongoing world economic developments, which may especially affect small open economies. Although there is currently no global statistical institute in charge of providing official quarterly national accounts at a global level, the IMF releases real GDP annual growth rate figures on an annual basis. However, the IMF releases its GDP figures only twice a year (usually in April and October), although there are two additional updates in January and July that provide much less detail.

Therefore, the recent literature has drawn some attention on certain indicators at higher frequencies, which are promptly available and are used to construct early estimates of the world GDP. Rossiter (2010) uses bridge equations to show that PMIs are useful for forecasting developments in the global growth. Within the bridge equation framework, Golinelli and Parigi (2014) detect that short-run indicators from advanced and emerging countries help in predicting the world variables and Drechsel et al. (2014) find that several monthly leading global indicators improve upon the world forecasts of the IMF. Ferrara and Marsilli (2014) develop a linear Dynamic Factor Model (DFM) to summarize the information of a large monthly database into small numbers of factors and use the MIDAS framework to show that they improve upon the IMF forecasts, at least at the beginning of each year.[1]

These approaches suffer from two limitations. The first limitation is that they focus on GDP on an annual basis while the IMF also releases GDP quarterly growth rates. In spite of the advantage in managing data on a quarterly basis, the IMF releases its quarterly figures sporadically, with long publication delays (9 months on average) and no fixed starting date. In addition, to the best of our knowledge, its longest available world GDP quarterly series begins in 2007, which clearly restricts the econometric analysis. To overcome this drawback, we extend the series back to 1991 by replicating the IMF methodology.[2] Both series are the same from 2007 up to the present, but our enlarged series dates back to 1991.

The second limitation of these approaches is that they all rely on linear specifications, which handicaps the models in capturing the nonlinearities that characterize the world business cycle fluctuations. To overcome this drawback, we propose an extension of the Markov-switching DFM (MS-DFM) suggested in Camacho et al. (2012). As in their proposal, the MS-DFM advocated by Kim and Yoo (1995), Chauvet (1998) and Kim and Nelson (1998) is enabled to deal with mixing frequencies, publication delays and different starting dates in the economic indicators. In this framework, low-frequency indicators are treated as high-frequency indicators with missing observations and the model is estimated by using a time-varying nonlinear Kalman filter. In addition, we extend the model to handle leading indicators, which are very useful in short-term forecasting (Camacho and

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[1] An interesting alternative Bayesian approach is the BVAR for the G-7 of Canova et al. (2007).

[2] The methodology is based on the aggregation of national quarterly growth rates of 69 countries, which are weighted by their share of GDP ppp in the world.

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Martinez-Martin, 2014) since they usually start to decline before the economy as a whole declines, and start to improve before the general economy begins to recover from a slump. We allow the data to select the number of periods by which the leading indicators lead the broad economic activity, from a minimum of one month to one and a half years.

In the empirical application, we use this extension to evaluate the accuracy of the model in computing short-term forecasts of world GDP and inferences about the state of the global economy. For this purpose, we estimate the MS-DFM with six economic indicators: the quarterly world GDP and the monthly global industrial production index, the global manufacturing Purchasing Manager Index (PMI), the employment index, the new export orders index and the CBOE volatility index (VIX). Using this approach, we develop a pseudo real-time forecasting exercise, where data vintages are constructed from successive enlargements of the latest available data set by taking into account the real-time data flow (and hence the publication lags). Therefore, the experiment tries to mimic as closely as possible the real-time analysis that would have been performed by a potential user of the models when forecasting, in each period, on the basis of different vintages of data sets. In line with the substantial publication delay of world GDP, in each forecast period we perform backcasts (predict the previous quarters before data for those quarters are released), nowcasts (predict the current period) and forecasts (predict the next quarter).

Our main results are as follows. First, the percentage of the variance of world GDP growth that is explained by our MS-DFM is slightly above 70%, indicating the high potential ability of our extension to explain global growth. Second, our business cycle indicator is in striking accord with the consensus of the history of the world business cycle (Grossman et al., 2014). Third, our pseudo real-time analysis shows that our MS-DFM clearly outperforms univariate forecasts, especially when backcasting and nowcasting. In addition, our MS-DFM also outperforms the forecasts of a linear DFM, although the gains mitigate. Fourth, we also compare the performance of the fully non-linear MS-DFM (one-step approach) with the "shortcut" of using a linear DFM to obtain a coincident indicator which is then used to compute the Markov-switching probabilities (two-step approach). In line with Camacho et al. (forthcoming), our results suggest that the one-step approach is preferred to the two-step approach to compute inferences on the business cycle phases.

The structure of this paper is organized as follows. Section 2 describes the methodological considerations of the model. Section 3 contains data descriptions and the main empirical results. Section 4 concludes.

2. The econometric model

To account for the peculiar characteristics of the data flow in real time, the comovements across the economic indicators and the business cycles asymmetries, we start from the approach suggested in Camacho et al. (2012). This model is extended to handle economic indicators that lead the broad economic activity.

2.1. Mixing frequencies

The approach deals with the problem of mixing monthly and quarterly frequencies of flow data by treating quarterly series as monthly series with missing observations. Let us assume that the levels of the quarterly flow variable in the quarter that ends in month t, G_t, can be decomposed as the sum of three unobservable monthly values X_t, X_{t-1}, and X_{t-2}, where t, $t-1$ and $t-2$ refer to the three months of that quarter

$$G_t = 3\frac{X_t + X_{t-1} + X_{t-2}}{3}. \tag{1}$$

Following the linear framework described in Mariano and Murasawa (2003), let us assume that the arithmetic means can be approximated by geometric means. Hence, the level of the quarterly flow variable becomes

$$G_t = 3(X_t X_{t-1} X_{t-2})^{1/3}. \tag{2}$$

Applying logs and taking the three-period differences for all t

$$\Delta_3 \ln G_t = \frac{1}{3}(\Delta_3 \ln X_t + \Delta_3 \ln X_{t-1} + \Delta_3 \ln X_{t-2}). \tag{3}$$

Calling $\Delta_3 \ln G_t = g_t$, and $\Delta \ln X_t = x_t$, and after a little algebra

$$g_t = \frac{1}{3}x_t + \frac{2}{3}x_{t-1} + x_{t-2} + \frac{2}{3}x_{t-3} + \frac{1}{3}x_{t-4}, \tag{4}$$

which shows that quarterly growth rates of the quarterly flow variable can be viewed as sums of underlying monthly growth rates of the underlying monthly series.

2.2. Dynamic properties

Let us assume that the n indicators included in the model, y_{it}, $i = 1., \ldots, n$, admit a dynamic factor representation. In this case, the indicators can be written as the sum of two stochastic components: a common component, f_t, which represents the overall business cycle conditions, and an idiosyncratic component, u_{it}, which refers to the particular dynamics of the series.

To account for the business cycle asymmetries, we assume that the underlying business cycle conditions evolve with $AR(p_f)$ dynamics, which is governed by an unobserved regime-switching state variable, s_t,

$$f_t = c_{s_t} + \theta_1 f_{t-1} + \ldots + \theta_{p_f} f_{t-p} + \varepsilon_{ft}, \tag{5}$$