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Estimating the output gap in real time: A factor model approach☆

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ABSTRACT

By using a dynamic factor model, we can substantially improve the reliability of real-time output gap estimates for the U.S. economy. First, we use a factor model to extract a series for the common component in GDP from a large panel of monthly real-time macroeconomic variables. This series is immune to revisions to the extent that revisions are due to unbiased measurement errors or idiosyncratic news. Second, our model is able to handle the unbalanced arrival of the data. This yields favorable nowcasting properties and thus starting conditions for the filtering of data into a trend and deviations from a trend. Combined with the method of augmenting data with forecasts prior to filtering, this greatly reduces the end-of-sample imprecision in the gap estimate. The increased precision has economic importance for real-time policy decisions and improves real-time inflation forecasts.

1. Introduction

The measurement of the output gap, that is, the difference between the economy's actual output and its potential trend level, is very imprecise in real time.[1] When additional information subsequently becomes available, one often sees large ex post revisions in the output gap. This poses a challenge for monetary policy, which depends on a correct real-time assessment of the current state of the economy.[2] Monetary policy actions based on an erroneous output gap estimate could destabilize the economy.

The reliability of estimates of the output gap in real time was first studied by Orphanides and van Norden (2002). They find, for a wide selection of methods applied to the U.S. economy that the uncertainty of the real-time estimates of the output gap is of the same magnitude as the gap itself. Cayen and van Norden (2005), Bernhardsen, Eitrheim, Jore, and Røisland (2005) and Marcellino and Musso (2011) find similar results for Canada, Norway and the Euro area, respectively.

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[1] Note that such an empirical measure of the output gap differs from the theoretical concept of the output gap used in DSGE models. In these models the output gap represents the deviation of output from its equilibrium level in the absence of nominal rigidities, see, e.g., Gali (2003).

[2] The use of ex post revised data may yield misleading descriptions of historical policy decisions. Several studies, see, e.g., Orphanides (2001), have shown that real-time policy recommendations differ considerably from those obtained with ex post revised data. See also Chauvet and Piger (2003, 2008) and Billio and Casarin (2010) for real-time analysis of the state of the economy, and Croushore and Stark (2001) and Croushore (2011) for a general overview of the advantages of using real-time data.

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There are several factors that complicate the measurement of the output gap in real time. Macroeconomic data are released with a substantial time delay, and important data series are subsequently revised when less timely information becomes available. Moreover, most methods of computing the output gap allow the trend of the GDP series, i.e., the proxy for potential output, to vary over time. Thus, in real time, it becomes challenging to allocate recent changes in the gap to changes *in* the trend or to deviations *from* the trend. That allocation will become more precise for one particular point in time when the subsequent observations become available. This end-of-sample problem, which is also often referred to as the endpoint problem, is an important source of real-time imprecision when estimating the output gap. In the aforementioned studies, attribution of the error to various causes indicates that the end-of-sample problem is the most important reason for the real-time estimation error. For a more detailed discussion of the end-of-sample problem, see Baxter and King (1999), Orphanides and van Norden (2002) and Mise, Kim, and Newbold (2005).

In this paper, we construct a novel large real-time data set[3] and study the potential of a dynamic factor model to improve the reliability of real-time output gap estimates through two mechanisms.

First, we proceed by using the factor model to extract a series for the common component in GDP from a large panel of related data. This series will be immune to revisions to the extent that revisions are due to unbiased measurement errors or idiosyncratic news. We use a dynamic factor model to moderate the effect of revisions, Garratt, Lee, Mise, and Shields (2008) attempt to model the revision process, or changes in vintages, through a co-integrating VAR model. Our approach is based on the alternative assumption that revisions are idiosyncratic in nature and do not display a systematic pattern. Indeed, we show that the factors obtained from the real-time data set and from the final data set are almost identical, thus producing close to identical GDP estimates. Next, we calculate the output gap of the common component series and show that this series is almost invariant to data revisions. Using the factor model in this way, we reduce the errors due to data revisions such that they are less than 10 percent of the revision errors in the standard approach. That factor models are robust to revision errors was conjectured in Giannone, Reichlin, and Small (2008).

Second, we address the end-of-sample problem by using the dynamic factor model to augment the time series of GDP with a nowcast. Following the work by Evans (2005) and Giannone et al. (2008), there has been a substantial interest in nowcasting, i.e., current quarter forecasting.[4] We use a monthly dynamic factor model similar to Giannone et al. (2008). The model is able to handle a 'jagged edge' in the data and incorporate new information on non-synchronized variables as they become available, i.e., it can handle the unbalanced arrival of the data,[5] which yields favorable nowcasting properties and, thus, starting conditions for the filtering of data into trend and deviations from trend. To the best of our knowledge, this is the first paper to substantiate the importance of high quality nowcasts for output gap estimations in a real-time data environment. We show that this information is, indeed, important for reducing the end-of-sample problem and for improving the reliability of real-time output gap estimates.

In addition, our approach can be combined with the augmentation method suggested by Mise et al. (2005). They show that augmenting the time series for GDP with forecasts up to 28 quarters ahead improves the Hodrick and Prescott (1997) (HP) filter estimate of the trend and cycle towards the last observations of the series.[6] We focus on the HP filter as the detrending method of choice because it is widely used, it is simple and it allows for time variation in the trend estimate.[7] The overall performance of our suggested approach reduces total errors to about 25 percent of that of the standard approach. Furthermore, as the output gap is unobservable, it is in general difficult to assess the quality of different estimates. Several papers therefore assess the quality of the output gap measures by studying how useful they are for inflation forecasting. We show that our output gap measure also increases forecasting performance of inflation relative to a univariate benchmark model. Although the improvements are modest, this finding contrasts the discouraging results of using output gap measures for inflation forecasting in Orphanides and van Norden (2005), Clark and McCracken (2006) and Marcellino and Musso (2011).

Finally, studies by Stock and Watson (1989), Chauvet and Piger (2008) and Altissimo, Cristadoro, Forni, Lippi, and Veronese (2010) use a factor model to construct a business cycle indicator. These papers interpret the business cycle as co-movements of many variables. Hence, the factors themselves (or a linear combination of the factors) can naturally be interpreted as the business cycle indicator. Our approach differs from these studies as we focus on how high quality nowcasts from a factor model can improve real-time estimates of standard measures of the output gap. However, we also check how useful business cycle indicators, measured as different factors, are for inflation forecasting.

This paper is organized as follows. In the following section, we present the factor model. Section 3 presents our data and discusses model selection issues. Empirical results are discussed in Section 4. We assess how much we can improve the reliability of output gap estimates in real time by first reducing the data revision problem and then by reducing the end-of sample problem, respectively. Section 5 illustrates the economic implications of our method. First, we study the contribution of different output gap measures in terms of inflation forecasting performance. We then study the magnitude of the interest rates implied by a simple Taylor rule using different output gap measures. Finally, in Section 6, we study the inflation forecasting performance when using business cycle indicators, and in Section 7, we summarize our findings and conclude our paper.

2. Econometric framework

Our econometric model combines a dynamic factor model with a standard detrending method to estimate the output gap in real time. More specifically, we use a monthly dynamic factor model to exploit information from a large data set in a timely matter. The monthly factor model provides a timely estimate of quarterly GDP. We then apply the HP filter to the estimated GDP series and

[3] Bernanke and Boivin (2003) and Giannone, Reichlin, and Sala (2005) also construct a large real-time data set and use a factor model in a forecasting exercise and to study monetary policy in real time, respectively.

[4] For more recent nowcasting applications, see Kuzin, Marcellino, and Schumacher (2011), Aastveit, Gerdrup, Jore, and Thorsrud (forthcoming) and Banbura, Giannone, Modugno, and Reichlin (2012).

[5] The jagged edge problem arises with differences in publication lags among the variables and results in an incomplete set of data for the most recent period. This causes a jagged edge at the end of the sample (see Wallis (2007)).

[6] While the HP filter yields an optimal decomposition of a time series into orthogonal components that can be regarded as "trend" and "cycle" at the center of a moderately long time series, the HP optimality do not apply to estimation of the cyclical component at the most recent time periods. Watson (2007) finds similar results when using the Band-pass filter for trend and cycle estimation.

[7] The output gap is unobservable. There is considerable uncertainty about how to calculate the gap as various methods exists. Although the various detrending methods may have different real time properties, this is a general problem when calculating output gaps. In this paper we abstract from this issue as we select the HP filter as our detrending method. For a comparison of different detrending methods and their real time properties, see Orphanides and van Norden (2002).