International Journal of Forecasting 29 (2013) 698–714

Contents lists available at ScienceDirect

International Journal of Forecasting

journal homepage: www.elsevier.com/locate/ijforecast

Forecasting with vector autoregressive models of data vintages: US output growth and inflation

Michael P. Clements [a], Ana Beatriz Galvão [b,*]

[a] Department of Economics, University of Warwick, Coventry, CV4 7AL, UK

[b] Queen Mary University of London, School of Economics and Finance, Mile End Road, E1 4NS, London, UK

ARTICLE INFO

Keywords:
Data revisions
Forecasting
Data uncertainty

ABSTRACT

Vintage-based vector autoregressive models of a single macroeconomic variable are shown to be a useful vehicle for obtaining forecasts of different maturities of future and past observations, including estimates of post-revision values. The forecasting performance of models which include information on annual revisions is superior to that of models which only include the first two data releases. However, the empirical results indicate that a model which reflects the seasonal nature of data releases more closely does not offer much improvement over an unrestricted vintage-based model which includes three rounds of annual revisions.

1. Introduction

The first or 'advance' estimates of national accounts data issued by statistical agencies are based on partial source data and are subject to revision. These estimates are typically revised many times. The initial revisions typically reflect the availability of more complete source data, while subsequent annual revisions incorporate new annual source data in the estimates. Finally, comprehensive or benchmark revisions make use of major periodic source data, as well as methodological and conceptual improvements.[1] From a policy perspective, these data revisions mean that there is a good deal of uncertainty about the true current (and recent past) state of the economy. In this paper, we present a real-time forecasting evaluation of data which are subject to revision. It is real time in the sense that, at each point in time, the forecasting models are specified and the parameters estimated using only data for time periods up to that point in time, *and* the vintages of data used are restricted to those which would have been available at that time.

Clements and Galvão (2011) show that a certain class of models can be used for forecasting 'fully-revised' or 'post-revision' values of past and future observations, and assess the value of such forecasts in terms of their contribution to improving real-time estimates of the output gap, trend inflation and the inflation gap.[2] We undertake a more detailed investigation of the forecasting performances of these models. Our interest is not only in forecasting post-revision values, we also consider their abilities to forecast observations of different maturities (from lightly-revised to fully-revised data) published at the same date (vintage).

The class of models which we consider are the vintage-based vector autoregressive (V-VAR) models of Garratt,

* Corresponding author. Tel.: +44 20 78828825.
E-mail addresses: m.p.clements@warwick.ac.uk (M.P. Clements), a.ferreira@qmul.ac.uk (A.B. Galvão).

[1] In the case of US National Accounts data, the Bureau of Economic Analysis provides descriptions of the methodologies employed at http://www.bea.gov/methodologies/index.htm#national_meth.

[2] Orphanides (2001) and Orphanides and van Norden (2002) show that estimates of the output gap based on final data can be markedly different from those available in real time, affecting both historical evaluations of monetary policy and the effective conduct of monetary policy in real time. Clements and Galvão (2011) show that real-time estimates of trend inflation and the inflation gap (computed using the model of Stock & Watson, 2007, 2010) will also differ from the historical estimates of these quantities.

0169-2070/$ – see front matter © 2012 International Institute of Forecasters. Published by Elsevier B.V. All rights reserved.
doi:10.1016/j.ijforecast.2011.09.003

Lee, Mise, and Shields (2008, 2009) and Hecq and Jacobs (2009). The key characteristic of these models is that the vector of variables being modelled consists of estimates of recent observations of the variable of interest from the current vintage of data. We consider a number of different VAR specifications for modelling data on each variable of interest—that is, inflation and output growth. One variant seeks to approximate the publication pattern of data releases by the statistical agency better. Another specification imposes restrictions which are consistent with the assumption that revisions published after the first revision are efficient, in the sense that they are not predictable based on past data vintages.

Our models focus on the role of past vintages of data in modelling and forecasting future data vintages, and in so doing we neglect the potential usefulness of explanatory variables. Much of the recent literature has looked at forecasting using large numbers of explanatory variables, as in the dynamic factor model literature (see, e.g., Stock & Watson, 2011, chap. 2), for a recent review), but has ignored the data revisions dimension by taking only the latest-available dataset at the time of the investigation. In principle, our approach could readily be extended to include explanatory variables which are subject to revision, so that the vector of variables being modelled could include the vintage estimates for a number of variables. In practice, the single-variable multiple-vintage VAR models already include a large number of parameters by considering a large number of estimates from each vintage, meaning that such extensions would probably be handled best within a Bayesian framework, with large numbers of parameters shrunk to prior values. We leave for future research the general question of whether explanatory variables, including the past vintages of data available for such variables, could be used for improving the forecasts of the quantities in which we are interested here.

In a recent review of forecasting with real-time data, Croushore (2006) found that the results of forecasting with state-space models which incorporate data revisions are mixed, compared to simply ignoring data revisions. Examples of multiple-vintage models include studies by Cunningham, Eklund, Jeffery, Kapetanios, and Labhard (in press), Garratt et al. (2008, 2009), Harvey, McKenzie, Blake, and Desai (1983), Hecq and Jacobs (2009), Howrey (1984), Jacobs and van Norden (2011) and Patterson (1995, 2003).

Based on the models we consider, our findings are more promising, especially for inflation. Our main contributions are as follows. For US output and inflation, we provide an extensive evaluation of vintage-based VAR model forecasts of a range of maturities of data using a variety of different 'actuals'. We distinguish between forecasting future observations and forecasting revisions to past data. We consider the performances of models which offer a 'better' characterisation of the release practices of the statistical agency, and explain, using a Monte Carlo, why the forecasts are no better than those produced using the unrestricted vintage-based VAR. We also assess the information content of annual revisions to these two key US macro variables.

The plan of the remainder of the paper is as follows. Section 2 describes the basic VAR model and the alternative versions. Section 3 is a detailed study of forecast performance, where we consider forecasts of a range of data maturities. In this section we also consider the imposition of cointegrating restrictions based on levels representations relative to specifying models in growth rates, and present a Monte Carlo which aims to illuminate some aspects of the empirical findings. Section 4 compares the V-VAR models with standard practices for forecasting both first-release[3] and latest-vintage actuals, as these are the mainstay of model forecast comparisons when data are subject to revision. Section 5 offers some concluding remarks.

2. The multiple-vintage VAR models

The models which we consider are related to the vintage-based VAR (V-VAR) of Hecq and Jacobs (2009) and the models of Garratt et al. (2008, 2009), and are described by Clements and Galvão (2011). Here we briefly describe those models, and a number of additional variants. These models assume that the data revision process can be modelled based only on observed components.[4]

We work with growth rates, so that y_t^{t+1} is the growth rate at period t computed using data from vintage $t + 1$. This corresponds to the BEA 'advance estimate', which we will call the first estimate, in order to avoid confusion. The advance estimate is made available toward the end of the first month of the following quarter. We use the real-time datasets of Croushore and Stark (2003), which record the data available in the middle of the second month of the following quarter, which corresponds to the advance estimate. Our second estimate, or first revised value, is y_t^{t+2}, which corresponds to the BEA 'final' estimate. A key characteristic of the BEA data releases is that the third estimate will be unrevised, i.e., $y_t^{t+3} = y_t^{t+2}$, unless $t + 3$ is the third quarter of a year, in which case the third estimate of y_t will incorporate an annual revision, and $y_t^{t+3} \neq y_t^{t+2}$. It is sometimes assumed that revisions after the first are essentially unpredictable. For example, Clark (2011) and Garratt et al. (2008) both use the BEA 'final' estimate (our y_t^{t+2}) as their actual values for computing forecast errors. Their choice of a target variable is based on the assumption that annual and benchmark revisions are generally unpredictable.

2.1. Unrestricted model

We begin by glossing over this institutional detail, and simply suppose that past and current vintages of data can be used to predict estimates published in future vintages.

3 Some studies use the estimates available two quarters after the reference quarter as the actuals, rather than the estimates available in the following quarter.

4 Examples of models with unobserved components include those of Cunningham et al. (in press) and Jacobs and van Norden (2011), *inter alia*. Kishor and Koenig (forthcoming) build on earlier contributions by Howrey (1978, 1984) and Sargent (1989) and use a Kalman filtering approach for estimating post-revisions values based on the current vintage of data.