Journal of Macroeconomics 34 (2012) 76–86

Contents lists available at SciVerse ScienceDirect

Journal of Macroeconomics

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

The limited usefulness of macroeconomic Bayesian VARs when estimating the probability of a US recession

Pär Österholm *

Monetary Policy Department, Sveriges Riksbank, 103 37 Stockholm, Sweden

ARTICLE INFO

Article history:
Received 8 April 2011
Accepted 27 October 2011
Available online 29 November 2011

JEL classification:
E17

Keywords:
Predictive density
Fan chart
Leading indicator
Survey data

ABSTRACT

The Bayesian VAR model provides a convenient tool for generating predictive densities and making probability statements regarding the future development of economic variables. This paper investigates the usefulness of standard macroeconomic Bayesian VAR models to estimate the probability of a US recession. Defining a recession as two quarters in a row of negative GDP growth, the probability is estimated for two quarters of the most recent US recession, namely 2008Q3–2008Q4. In contrast to judgemental probabilities from this point in time, it is found that the BVAR assigns a very low probability to such an event. This is true also when survey data, which generally are considered as good leading indicators, are included in the models. We conclude that while Bayesian VAR models are good forecasting tools in many cases, the results in this paper raise question marks regarding their usefulness for predicting recessions.

1. Introduction

As a part of the decision making process, economic agents have to assign probabilities to certain developments in the economy. These probabilities are rarely communicated but a number of central banks – such as the Bank of England, Norges Bank and Sveriges Riksbank – regularly publish fan charts for several macroeconomic variables. Such fan charts can be used to answer a number of probability questions, where focus historically has been on the evolution of future inflation.

Recently, it has been argued that predictive densities from VAR models can be used to make probability statements; see, for example, Garratt et al. (2003), Leeper and Zha (2003) and Österholm (2009). While this clearly is a convenient approach, a highly relevant question to ask before adopting it is whether the estimated probabilities are reasonable and thereby useful in, for example, policy analysis. The purpose of this paper is hence to scrutinise the probability statements from standard macroeconomic VAR models when it comes to an issue of general interest to forecasters and decision makers, namely the US economy being in a recession.

Relying on VAR models, the NBER's classification of recessions is not particularly useful and we will instead use the commonly employed definition of two quarters of negative GDP growth in a row.[1] We will focus on two quarters of the most recent US recession, namely 2008Q3–2008Q4, both of which are associated with fairly large negative values of GDP growth. It is difficult to evaluate the estimated recession probabilities from the model using a formal criterion since *ex post*, the probability of the recession taking place is (close to) one.[2] The approach taken here will hence be to relate the estimated probabilities to judgemental forecasts made around the relevant time point. For example, former chairman of the Federal Reserve, Alan

* Tel.: +46 8 787 0162.
E-mail address: par.osterholm@riksbank.se

[1] See, for example, Filardo (1999) and Lahiri and Wang (2006) for other papers using the same definition and McNees (1991) for criticism of it.

[2] Revisions of the GDP series could potentially change this fact.

0164-0704/$ - see front matter
doi:10.1016/j.jmacro.2011.10.002

Greenspan said in May 2008 in Financial Times that the probability of a recession was larger than 50% and in August 2008, In-Trade recession bet put the probability of a recession close to 30%. In a similar spirit, it was mentioned at the budget briefing on the 24th of October 2008 that "*according to Moody's Economy.com, the probability of a national recession increased to 43 percent in August compared with 35 percent in July*". If the models generate recession probabilities that are substantially lower than these numbers, it is a reason to be concerned regarding the properties of the model.

Several models are estimated and evaluated. The two benchmark models are (i) a univariate Bayesian AR model for GDP growth and (ii) a trivariate Bayesian VAR model with GDP growth, CPI inflation and the three month treasury bill rate. Both of these specifications are commonly used in empirical work and particularly the popularity of small models – including a measure of real activity, inflation and a nominal interest rate – cannot be overstated in macroeconomic analysis and forecasting; see, for example, Clarida et al. (1999), Rudebusch and Svensson (1999), Cogley and Sargent (2001), Primiceri (2005), Ribba (2006), Rubaszek and Skrypczynski (2008) and Berger and Österholm (2009).

Results show that the benchmark models assign very low probabilities to a recession at the investigated time point and the analysis indicates that this is due to the dynamic properties of the model. In an attempt to see whether the usage of leading indicators can improve the estimated probabilities, we augment the benchmark models with a number of variables. Three variables based on survey data are used: the University of Michigan Consumer Sentiment Index, the Institute for Supply Management PMI Composite Index and a measure of bank lending tightening from the Board of Governors of the Federal Reserve's Senior Loan Officer Survey on Bank Lending Practices. Finally, we augment the models with oil price changes. However, despite the popularity of these variables, only some of them show evidence of marginally being able to improve the models' recession-prediction ability. None of the estimated models generate recession probabilities that are even close to the judgemental probabilities.

The rest of this paper is organised as follows. Section 2 briefly presents the Bayesian VAR model used for the estimation. In Section 3, data are described and the forecasting performance of the benchmark and augmented models is investigated. We also conduct some sensitivity analysis. Finally, Section 4 concludes.

2. Methodology

The forecasting tool used for the analysis in this paper is a state-of-the-art Bayesian VAR (BVAR) model developed by Villani (2009).[3] The model is given by

$$\mathbf{G}(L)(\mathbf{x}_t - \boldsymbol{\mu}) = \boldsymbol{\eta}_t, \tag{1}$$

where $\mathbf{G}(L) = \mathbf{I} - \mathbf{G}_1 L - \ldots - \mathbf{G}_p L^p$ is a lag polynomial of order p, $\mathbf{x}_t$ is an nx1 vector of stationary macroeconomic variables, $\boldsymbol{\mu}$ is an nx1 vector describing the steady-state values of the variables in the system and $\boldsymbol{\eta}_t$ is an nx1 vector of *iid* error terms fulfilling $E(\boldsymbol{\eta}_t) = \mathbf{0}$ and $E(\boldsymbol{\eta}_t \boldsymbol{\eta}_t') = \boldsymbol{\Sigma}$.

The prior on $\boldsymbol{\Sigma}$ is given by $p(\boldsymbol{\Sigma}) \propto |\boldsymbol{\Sigma}|^{-(n+1)/2}$. Regarding the dynamics of the model, the prior on $vec(\mathbf{G})$ – where $\mathbf{G} = (\mathbf{G}_1 \quad \ldots \quad \mathbf{G}_p)'$ – is given by $vec(\mathbf{G}) \sim N_{pn^2}(\boldsymbol{\theta}_{\mathbf{G}}, \boldsymbol{\Omega}_{\mathbf{G}})$ and is of Minnesota style. The Minnesota prior (Litterman, 1986) takes its starting point in the observation that a univariate random walk (potentially with drift) is a reasonably good forecasting model for the level of many macroeconomic variables. Hence, for a model with variables in levels, a prior mean on the first own lag equal to 1 and 0 on all other coefficients in $\mathbf{G}$ is used in the traditional specification of this prior. However, this is theoretically inconsistent with the mean-adjusted model in Eq. (1), as a random walk does not have a well-specified unconditional mean. The prior is therefore modified so that the prior mean on the first own lag is set equal to 0.9 for variables that are modelled in levels and 0 for variables modelled in differences. The tightness is adjusted through a number of hyperparameters. Coefficients on long lags have smaller variances than those on short lags and the variances on cross-lag coefficients are smaller than those on own-lag coefficients. This is achieved by setting the overall tightness to 0.2, cross-equation tightness to 0.5 and choosing a lag decay parameter of 1.[4] For $\boldsymbol{\mu}$, priors are given by $\boldsymbol{\mu} \sim N_n(\boldsymbol{\theta}_{\boldsymbol{\mu}}, \boldsymbol{\Omega}_{\boldsymbol{\mu}})$. We return to the specific values chosen in Sections 3.2 and 3.4.

The numerical evaluation of the posterior distribution is conducted using the Gibbs sampler with the number of draws set to 10,000. The forecasts from the models are generated in a straightforward manner. For every draw from the posterior distribution, a sequence of shocks is drawn and used to generate future data. In this way we generate a multivariate predictive density (which contains 10,000 paths for each variable in the system). This setup means that it is easy to answer questions regarding the model's estimated probability of certain events taking place. In this paper, we are interested in the probability of the next two quarters both having negative GDP growth – that is, we want to find Pr $(\Delta y_{t+1} < 0 \cap \Delta y_{t+2} < 0)$. This is done by simply finding the number of paths in the predictive density where growth is predicted to be negative in both of the two following quarters and dividing that number with the number of draws in the Gibbs sampling algorithm (that is, 10,000).

The simplicity with which probabilities can be calculated is obviously highly appealing to forecasters, policymakers and other economic agents. Depending on the variables included in the model, many different questions can be answered. For example, a central bank might be interested in finding out what the probability of inflation being below target two years

[3] This has the usual benefits of BVAR models – such as reducing the problem of over-parameterisation – but has the additional advantage that it also allows for an informative steady state prior to be specified, a property which has been shown to further improve forecasting performance; see, for example, Adolfson et al. (2007), Österholm and Zettelmeyer (2008), Villani (2009) and Beechey and Österholm (2010).

[4] These are values recommended by Doan (1992) which are commonly used in empirical work; see, for example, Villani (2009). See Litterman (1986) for a discussion regarding the hyperparameters.