Available online at www.sciencedirect.com
ScienceDirect
International Journal of Forecasting 27 (2011) 512–528
international journal of forecasting
www.elsevier.com/locate/ijforecast

Open economy forecasting with a DSGE-VAR: Head to head with the RBNZ published forecasts

Kirdan Lees[a,*], Troy Matheson[b], Christie Smith[a,1]

[a] Reserve Bank of New Zealand, 2 the Terrace, Wellington 6011, New Zealand
[b] International Monetary Fund, 700 19th Street, N.W., Washington DC 20431, United States

Abstract

We construct a DSGE-VAR model for competing head to head with the long history of published forecasts of the Reserve Bank of New Zealand. We also construct a Bayesian VAR model with a Minnesota prior for forecast comparison. The DSGE-VAR model combines a structural DSGE model with a statistical VAR model based on the in-sample fit over the majority of New Zealand's inflation-targeting period. We evaluate the real-time out-of-sample forecasting performance of the DSGE-VAR model, and show that the forecasts from the DSGE-VAR are competitive with the Reserve Bank of New Zealand's published, judgmentally-adjusted forecasts. The Bayesian VAR model with a Minnesota prior also provides a competitive forecasting performance, and generally, with a few exceptions, out-performs both the DSGE-VAR and the Reserve Bank's own forecasts.

Keywords: DSGE; Vector autoregression models; Macroeconomic forecasting; Open economy; Bayesian methods

1. Introduction

Combining models has been demonstrated to improve forecasts in a number of contexts (see for example Elliott & Timmermann, 2005; Goodwin, 2000; and Hall & Mitchell, 2007). Often this combination has been restricted to purely statistical models, rather than models developed from either microeconomic or macroeconomic theory. At the same time, policymakers often want structural models to assess alternative policies in the light of the Lucas critique, which stresses the dependence of reduced form parameters on control parameters set by policymakers.

Del Negro and Schorfheide (2004) show how a structural Dynamic Stochastic General Equilibrium (DSGE) model can be combined with a vector autoregression (VAR) to provide a hybrid, DSGE-VAR model that forecasts well and provides structure that policymakers can use to evaluate alternative policies. While Bayesian VARs utilise time series priors to help improve the forecasting performances

* Corresponding author. Tel.: +64 4 4713666.
E-mail addresses: kirdan.lees@rbnz.govt.nz (K. Lees), TMatheson@imf.org (T. Matheson), christie.smith@rbnz.govt.nz (C. Smith).
[1] Tel.: +64 4 4713740.

0169-2070/$ - see front matter
doi:10.1016/j.ijforecast.2010.01.008

of unrestricted VARs, the DSGE-VAR utilises macroeconomic theory to provide the priors. Equally, including the VAR component in the hybrid model helps to reduce the potential misspecification imposed on the data by the DSGE model.

In this paper we apply the DSGE-VAR methodology to New Zealand – a small, open economy with an inflation-targeting central bank. We estimate the five-variable DSGE model developed by Lubik and Schorfheide (2007) over the majority of the inflation targeting history of the Reserve Bank of New Zealand, since New Zealand has the longest such history of any explicit inflation targeter. The Lubik and Schorfheide (2007) DSGE model represents a minimal set of DSGE theory to apply to the data, and our VAR, based on the set of observables implied by the DSGE model, acts to mitigate any potential misspecification.

Since the Reserve Bank's many published forecasts over time are predicated on *endogenous* policy, they provide a unique benchmark amongst explicit inflation targeters against which to compare our DSGE-VAR forecasts. Because these forecasts are free to condition on *any* information set deemed relevant by the Reserve Bank (such as high frequency financial data, survey data, anecdotal evidence, institutional knowledge, or simply policymaker beliefs), these forecasts should set a relatively high benchmark for the DSGE-VAR, compared to, say, a random-walk, or the simple single-equation forecasting models that are frequently used as points of comparison for macroeconomic forecasting.

The rest of the paper is organised as follows. Section 2 discusses the DSGE-VAR technology and outlines the Del Negro-Schorfheide algorithm we adopt as our estimation procedure. Section 3 outlines the Lubik and Schorfheide model, our parameter estimates, and the impulse responses implied by the model. Section 4 compares the out-of-sample forecasts of the DSGE-VAR to the official forecasts of the Reserve Bank of New Zealand. Concluding comments are made in Section 5.

2. DSGE-VARs

Wold (1938) demonstrated that covariance-stationary processes have an infinite order moving average (MA) representation. If suitable restrictions prevail, infinite order MA processes can be represented using either autoregressive moving average models (ARMAs) or autoregressions (ARs). Multivariate analogues for vector-valued stochastic processes parallel the univariate relationships between MAs, ARMAs, and ARs.

It has long been recognised that theoretical models imply restricted forms for statistical models such as vector autoregressions or vector autoregressive moving average (VARMA) models. The correspondence between theoretical and statistical models has prompted interest in using theoretical models as the source of priors for their statistical counterparts. Ingram and Whiteman (1994) show that the prior from an RBC model can help to forecast key US macroeconomic variables. DeJong, Ingram, and Whiteman (2000) emphasize that Bayesian methods can be used to learn about the theoretical models.

Working in this vein, Del Negro and Schorfheide (2004) develop an estimation methodology that allows researchers to learn about theoretical models from their statistical counterparts.[2] Specifically, Del Negro and Schorfheide (2004) use a small dynamic stochastic general equilibrium (DSGE) model to provide priors for a VAR. The DSGE model incorporates rational, forward-looking agents who maximise their welfare subject to the constraints they face. By confronting the DSGE prior with the VAR, one can obtain a posterior distribution for the parameters of the DSGE model.

Del Negro and Schorfheide's approach can be thought of as generating artificial data by using the DSGE model to extend the sample of actual data. The VAR is then applied to this augmented data sample. The number of data observations generated by the DSGE model determines the influence which the DSGE model will have on the VAR. If more data are simulated from the DSGE model, it will have a greater influence on the parameter estimates obtained from the VAR. A key hyperparameter λ determines the weight attached to the theoretical DSGE model.[3] Del Negro and Schorfheide optimise this parameter to maximise the marginal data density (see Del Negro & Schorfheide, 2004, for further details).

[2] See Del Negro and Schorfheide (2003) for an overview of the methods and an application to US data. Gauss code is kindly made available at http://www.econ.upenn.edu/schorf/research.htm.

[3] For Bayesian VARs with a Minnesota prior, the corresponding hyperparameter is denoted by ι.