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A small-scale DSGE-VAR model for the Romanian economy

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ABSTRACT

This paper describes the theoretical structure and the estimation results for a DSGE-VAR model for the Romanian economy, an inflation targeting country since 2005. Having as benchmark the New-Keynesian model of Rabanal and Rubio-Ramirez (2005), the main additional feature introduced refers to the extension to a small open economy setting in order to account for this specific aspect of the Romanian economy.

Within the inflation targeting monetary policy regime, forecasts of central macro variables, inflation in particular, play an important part. Because inflation reacts to monetary measures with a considerable lag, the central bank's policy has to be forward-looking. Based on univariate measures of forecast performance, it is shown that the VAR with DSGE model prior produces forecasts that improve on those obtained using an unrestricted VAR model and the popular Minnesota prior in case of inflation, real exchange rate and nominal interest rate. Moreover, the DSGE-VAR model is informative about the structure of the economy and can help the "story-telling" in the central banks.

1. Introduction

In the last decades, inflation targeting has been adopted by an increasing number of central banks as their monetary policy framework. Due to the delays in the monetary policy transmission mechanism, central banks with quantitative inflation targets, Romania included, must have adequate tools to form views on future macroeconomic performance, especially on inflation prospects.

The vector autoregression models (VARs), introduced by Sims (1980), have long proven to be an effective method for modelling the dynamics of macroeconomic variables as well as forecasting. The VAR is an econometric model used to capture the linear interdependencies among multiple time series, the only prior knowledge required being a list of variables which can be hypothesized to affect each other intertemporally. In theory, the idea is to let the data guide the views regarding the true data generating process. In practice, however, the parameters in the VAR models are often not very precisely estimated using classical econometrics procedures due to the dimensionality problem: high number of parameters to be estimated using a limited number of observations. Therefore, alternative methods for estimating the coefficients in a VAR model have been developed, the most successful being the Bayesian approach, originally advocated by Litterman (1979). The Bayesian estimation method provides a logical and formally consistent way of introducing shrinkage by treating the parameters of the model as random variables with probability distributions which are used to summarize the status of the knowledge about each parameter (prior information). By combining the prior information with the information contained in the data (the likelihood function), an updated distribution for the parameters is obtained, known as the posterior distribution, which is used to carry inference about the value of the parameters. Thus, to the extent that the prior is based on non-sample information, the Bayesian approach offers a good framework for containing different sources of information when performing macroeconomic analysis. Karlsson (2013) provides a coherent survey on Bayesian approaches to inference in VAR models. Del Negro and Schorfheide (2011) and Koop and Korobilis (2009) present complementary reviews of Bayesian VAR models.

Even though it is proved that the Bayesian VAR model is a reliable forecasting tool (see, for example, Kinal and Ratner, 1986; Litterman, 1980 etc.), the specific functions of a central bank imply the usage of models that are based on much more economic theory than a VAR model and are thus useful as a "story-telling" device. The large scale-models that were used by central banks in the 1950s to 1970s were criticized because of the lack of microeconomic foundations, which made them subject to the Lucas critique (Lucas, 1976), as well as ad-hoc econometric restrictions. As a result, a new class of models have emerged, i.e. the dynamic stochastic general equilibrium (DSGE) models, built in recent years along the lines of New-Keynesian Economics. The DSGE models are microfounded, having a consistent behavioural structure which helps interpretation. Moreover, the structural parameters that govern the relations between the variables in a DSGE model are invariant to changes in economic policy, so, in

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principle, not subject to the Lucas critique. However, according to the empirical evidence, the DSGE models forecasts are usually dominated by univariate or multivariate time series models (see, among others, Del Negro and Schorfheide, 2013) and, therefore, many central banks are still reticent in adopting a DSGE model as the main tool for supporting the policy making.

In their seminal works, DeJong et al. (1993) and Ingram and Whiteman (1994) present an estimation methodology that unifies the two approaches mentioned above. DeJong et al. (1993) examine the impulse response functions generated by a VAR model estimated subject to the restrictions imposed by a monetary general equilibrium model, while Ingram and Whiteman (1994) demonstrate that prior information from a real business cycle model helps improve the forecasting performance in the case of movements in consumption, output, hours and investment for the US economy. Del Negro and Schorfheide (2004) significantly extend the earlier work: first, by showing how posterior inference for the VAR parameters can be translated into posterior inference for the DSGE model parameters, secondly by constructing a VAR identification scheme for the structural shocks based on a comparison of the contemporaneous VAR responses to shocks with the DSGE model responses and, finally, by illustrating how a VAR with DSGE model prior can be used to predict the effects of a permanent change in the policy rule. Lees et al. (2007) complement the analysis of a DSGE-VAR forecasting performance for the economy of New Zeeland along policy dimension: they use the estimated DSGE-VAR structure to identify optimal policy rules that are consistent with the Reserve Bank's Policy Targets Agreement. Other empirical applications of the DSGE-VAR methodology include Warne et al. (2013) for euro area, Bache et al. (2010) for Norway, Watanabe (2009) for Japan, Liu et al. (2007) for South Africa, etc.

This paper describes the theoretical structure and the estimation results for a DSGE-VAR model for the Romanian economy. The New-Keynesian model of Rabanal and Rubio-Ramirez (2005) is adopted, which serves as a minimal set of theory for modelling an inflation targeting economy. The model is extended to a small open economy setting in order to account for this specific feature of the Romanian economy. The forecasting performance of the DSGE-VAR model is evaluated against other VAR alternatives, i.e. an unrestricted VAR model and a VAR model with a Minnesota prior.

The rest of the paper is structured as follows. Section 2 briefly discusses the DSGE-VAR methodology. Section 3 presents the DSGE model used to construct prior beliefs about the VAR parameters, the data and the estimation results. Section 4 compares forecasts of the DSGE-VAR model to those obtained using the other VAR alternatives. Finally, Section 5 concludes.

2. The DSGE-VAR methodology

This section briefly presents the DSGE-VAR methodology and outlines the Del Negro-Schorfheide algorithm used in the estimation procedure.

As mentioned in the Introduction section, the idea of the DSGE-VAR approach is to use the DSGE model to construct prior distributions for the VAR parameters.

The starting point for the estimation is an unrestricted VAR of order l:

$$y_t = A_0 + A_1 y_{t-1} + A_2 y_{t-2} + \cdots + A_l y_{t-l} + u_t, \tag{1}$$

where $t=1,2,\ldots,T$. $y_t=(y_{1t},y_{2t},\ldots,y_{nt})$ is a $n\times 1$ vector of observable variables, A_0 is a $n\times 1$ vector of constant terms, $A_1,A_2,\ldots,A_n$ are $n\times n$ matrices of autoregressive parameters and $u_t=(u_{1t},u_{2t},\ldots,u_{nt})$ is a vector of residuals following a multivariate normal distribution, i.e. $u_t\sim N(0,\Sigma_u)$. T is the size of the sample used for estimation. The model for the whole data set can be reformulated as:

$$Y = XA + U \tag{2}$$

where $Y=\begin{bmatrix} y_1' \\ y_2' \\ \vdots \\ y_{T-1}' \\ y_T' \end{bmatrix}$, $X=\begin{bmatrix} 1 & y_0' & \cdots & y_{2-l}' & y_{1-l}' \\ 1 & y_1' & \cdots & y_{3-l}' & y_{2-l}' \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 1 & y_{T-2}' & \cdots & y_{T-l}' & y_{T-1-l}' \\ 1 & y_{T-1}' & & y_{T+1-l}' & y_{T-l}' \end{bmatrix}$, $A=\begin{bmatrix} A_0' \\ A_1' \\ \vdots \\ A_{l-1}' \\ A_l' \end{bmatrix}$

and $U=\begin{bmatrix} u_1' \\ u_2' \\ \vdots \\ u_{T-1}' \\ u_T' \end{bmatrix}$. The system described by Eq. (2) is characterized by the following likelihood function:

$$p(Y/A,\Sigma_u) = \left|\Sigma_u\right|^{-T/2} exp\left\{-\frac{1}{2}\mathrm{tr}\left[\Sigma_u^{-1}(Y'Y - A'X'Y - Y'XA - A'X'XA)\right]\right\} \tag{3}$$

The prior distribution for the VAR parameters is based on the DSGE model representation as a reduced-form VAR,[1] characterized by a likelihood function similar with the one presented in Eq. (3), $p(Y(\xi)/A,\Sigma_u)$, where ξ represents the vector of structural parameters from the DSGE model.

Loosely speaking, imposing the prior from the DSGE model implies the augmentation of the dataset by a number of $T^*=\lambda T$ "artificial" observations, (Y^*,X^*), generated using the DSGE model, where λ is a hyper-parameter representing the ratio of "artificial" data relative to the size of the actual sample of data. The likelihood function for the combined sample of "artificial" and actual observations is obtained by pre-multiplying $p(Y/A,\Sigma_u)$ with $p(Y^*(\xi)/A,\Sigma_u)$, where the term $p(Y^*(\xi)/A,\Sigma_u)$ can be interpreted as a prior density for A and Σ_u of the Inverted Wishart (IW) – Normal (N) form, conditional on the vector of structural parameters ξ:

$$\Sigma_u/\xi \sim IW\left(\lambda T\Sigma_u^*(\xi), \lambda T - k, n\right) \tag{4}$$

$$A/\Sigma_u, \xi \sim N\left(A^*(\xi), \Sigma_u \otimes \left(\lambda T\Gamma_{XX}^*(\xi)\right)^{-1}\right)$$

$A^*(\xi)$ and $\Sigma_u^*(\xi)$ are maximum likelihood estimators based on the sample of "artificial" data generated using the DSGE model.

As Del Negro and Schorfheide (2004) demonstrated, the posterior distribution of the VAR parameters is also of Inverted Wishart-Normal form:

$$\Sigma_u/Y, \xi \sim IW\left((\lambda+1)T\widetilde{\Sigma}_u(\xi), (\lambda+1)T - k, n\right) \tag{5}$$

$$A/Y, \Sigma_u, \xi \sim N\left(\widetilde{A}(\xi), \Sigma_u \otimes \left(\lambda T\Gamma_{XX}^*(\xi) + X'X\right)^{-1}\right)$$

where

$$\widetilde{A}(\xi) = \left(\lambda T\Gamma_{XX}^*(\xi) + X'X\right)^{-1}\left(\lambda T\Gamma_{XY}^*(\xi) + X'Y\right) \tag{6}$$

$$\widetilde{\Sigma}_u(\xi) = \frac{1}{(\lambda+1)T}\Big[\left(\lambda T\Gamma_{YY}^*(\xi) + Y'Y\right) - \left(\lambda T\Gamma_{YX}^*(\xi) + Y'X\right) \left(\lambda T\Gamma_{XX}^*(\xi) + X'X\right)^{-1}\left(\lambda T\Gamma_{XY}^*(\xi) + X'Y\right)\Big]$$

represent maximum likelihood estimates of A and Σ_u, based on the combined sample of actual observations and "artificial" observations generated using the DSGE model. In the estimation, in order

[1] Giacomini (2013) presents a literature review on the econometric relationship between DSGE and VAR models from the point of view of estimation and model validation.