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A DSGE-VAR model for forecasting key South African macroeconomic variables

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ABSTRACT

The paper develops a Small Open Economy New Keynesian DSGE-VAR (SOENKDSGE-VAR) model of the South African economy, characterised by incomplete pass-through of exchange rate changes, external habit formation, partial indexation of domestic prices and wages to past inflation, and staggered price and wage setting. The model is estimated using Bayesian techniques on data from the period 1980Q1 to 2003Q2, and then used to forecast output, inflation and nominal short-term interest rate for one-to eight-quarters-ahead over an out-of sample horizon of 2003Q3 to 2010Q4. When the forecast performance of the SOENKDSGE-VAR model is compared with an independently estimated DSGE model, the classical VAR and six alternative BVAR models, we find that, barring the BVAR model based on the SSVS prior on both VAR coefficients and the error covariance, the SOENKDSGE-VAR model is found to perform competitively, if not, better than all the other VAR models.

1. Introduction

Recent studies, namely, Liu and Gupta (2007), Liu et al. (2009, 2010), Gupta and Kabundi (2010, 2011) and Alpanda et al. (2011), have initiated a growing interest in forecasting macroeconomic variables in South Africa using Dynamic Stochastic General Equilibrium (DSGE) models.[1] However, in general, the studies find it difficult to outperform the atheoretical Vector Autoregressive (VAR) models, especially its Bayesian variant (BVAR) based on the Minnesota prior. These studies tend to attribute the relatively poor performance of the DSGE models to the fact that the frameworks of these models are not sophisticated enough, in the sense, that they, perhaps, do not incorporate the real and nominal rigidities to an appropriate extent to correctly capture the true dynamics of the data characterising the South African economy.[2]

Against this backdrop, we develop a Small Open Economy New Keynesian DSGE-VAR (hereafter SOENKDSGE-VAR) model of the South African economy, characterised by incomplete pass-through of exchange rate changes, external habit formation, partial indexation of domestic prices and wages to past inflation, and staggered price and wage setting. This model makes use of the structural framework of the theoretical DSGE to alleviate concerns relating to potential in-sample overfitting, while retaining the flexibility of VAR models, which often produce improved out-of-sample forecasting results. In addition, by incorporating the theoretical structure of a DSGE model, which seeks to describe the theoretical time-invariant behaviour of economic agent, the SOENKDSGE-VAR model would not be subject to the Lucas critique (Lucas, 1976).[3] Our decision to use a DSGE-VAR approach, over and above an independently estimated DSGE model, as done in the previous studies on South Africa, is motivated not only because of the fact that VAR models have tended to outperform DSGE model forecasts for the country, but also because of the available international evidence of DSGE-VAR models producing forecasts which are competitive, and at time substantially better, than the standard benchmark of VAR and BVAR models.[4]

The DSGE-VAR approach, as proposed by Del Negro and Schorfheide (2004), could be implemented by using a DSGE model to simulate time-series data, which is often used to populate parameter values in an unrestricted VAR model. In practice, the sample moments of the simulated data is replaced by the population moments computed from the

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[1] See also Ortiz and Sturzenegger (2007), Steinbach et al. (2009), Alpanda et al. (2010a,b) for in-sample analysis of business cycle properties of South Africa using DSGE models.

[2] This line of thinking was proposed by Smets and Wouters (2007) and is vindicated to some extent by Alpanda et al. (2011), wherein the authors develop a relatively elaborate DSGE model to produce competitive forecasts in relation to VAR-type models.

[3] This would be the case where it can be shown that the prior from the DSGE model influences the final results.

[4] See for example Del Negro and Schorfheide (2004, 2006), Del Negro et al. (2007), Hodge et al. (2008) and Lees et al. (2011).

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DSGE model solution. Given that the DSGE model depends on unknown structural parameters, one uses a hierarchical prior, which involves placing a specific distribution on the DSGE models parameters. A tightness parameter (λ), which is estimated by maximising the joint density of the data and the parameters, controls the weight of the DSGE model prior relative to the weight of the actual sample, with the values of 0, ∞ and 1 implying an unrestricted VAR, an independently estimated DSGE model[5] and a DSGE-VAR model with equal weight being given to the DSGE and the VAR.[6] Finally, Markov Chain Monte Carlo (MCMC) methods are used to generate draws from the joint posterior distribution of the VAR and DSGE model parameters.

The model is estimated using Bayesian techniques on data for South Africa and the United States (US) from the period 1980Q1 to 2003Q2, and then used to forecast output, inflation and a measure of nominal short-term interest rate for one- to eight-quarters-ahead over an out-of-sample horizon of 2003Q3 to 2010Q4. With South Africa moving to a flexible exchange rate regime in 1979, the starting point of the in-sample was obvious, while, the beginning of the out-of-sample horizon is chosen to correspond with the period when the inflation rate reverted back to the inflation targeting band of 3% to 6%. In February of 2000, the Minister of Finance, announced that the sole objective of the South African Reserve Bank (SARB) will be to achieve and maintain price stability.[7] In this regard, the SARB would pursue a goal to ensure that the inflation is within the target band by the end of 2002. With the target band being achieved in 2003Q2, we decided to use 2003Q3 as the starting date of our out-of-sample forecasting exercise. Note that, the endpoint of the sample is purely driven by data availability at the time this paper was written.

The forecast performance of the SOENKDSGE-VAR model is then compared with an independently estimated DSGE model, the classical VAR and BVAR models, with the latter being estimated based on six alternative priors, namely, Non-Informative and Informative Natural Conjugate priors, the Minnesota prior, Independent Normal–Wishart Prior, Stochastic Search Variable Selection (SSVS) prior on VAR coefficients and SSVS prior on both VAR coefficients and error covariance. After comparing the forecasts from the independently estimated DSGE and the DSGE-VAR models, we can determine exactly where the gains in the forecasting performance relative to standard benchmarks (if any), emanate from, i.e., whether it is because of the DSGE framework or due to estimation of the model based on the DSGE-VAR approach or both. To the best of our knowledge, this is the first attempt in forecasting key variables of the South African economy using a DSGE-VAR approach. In addition, we go beyond the convention in the forecasting literature of DSGE models, by incorporating BVAR models estimated under a wider set of prior assumptions (besides the Minnesota prior).

The remainder of the paper is organised as follows: Respective sections under Section 2 lay out the estimation methodology of the DSGE-VAR model, a discussion on the DSGE framework, data, the priors imposed on the DSGE model parameters and the estimation results. Section 3 presents the basics of the alternative forecasting models, while, Section 4 compares the performance of the DSGE-VAR model relative to an independently estimated DSGE model, the classical VAR and the BVAR under six alternative prior assumptions. Finally, Section 5 concludes.

2. Estimation methodology, model, priors, data and posterior estimates of the DSGE model

2.1. The basics of the DSGE-VAR approach

This section provides a brief overview of the methodology used to estimate the DSGE-VAR model, and follows closely the discussion in Del Negro and Schorfheide (2004).

Let the parameters of the DSGE model, which we describe in the next subsection, be denoted by the vector θ. Let y_t denote the column vector of n observable variables, which are also the variables included in the VAR. That is,

$$y_t = \Phi_0 + \Phi_1 y_{t-1} + \Phi_2 y_{t-2} + \ldots + \Phi_p y_{t-p} + u_t, \tag{1}$$

where: Φ_0 is a vector of constants; $\Phi_{1 \ldots p}$ are matrices of VAR parameters; and $u_t \sim N(0, \Sigma_u)$. This can be written more compactly as $Y = X\Phi + U$, where: Y and U are matrices with rows y_t' and u_t' respectively; X has rows 1, y_{t-1}', y_{t-2}', …, y_{t-p}' and $\Phi \equiv [\Phi_0, \Phi_1, \Phi_2, \ldots, \Phi_p]'$. It is noteworthy that the number of parameters in the DSGE model is much smaller than that in the VAR, hence the VAR tends to have a greater ability to fit the data.

As in Del Negro and Schorfheide (2004), we want to use a DSGE model to provide information about the parameters of the VAR. One way of doing this would be to simulate data from the DSGE and to combine it with the actual data and then estimate the VAR, with λ governing the relative weight placed on the prior information, since it is a measure of the relative share of simulated observations compared to the actual data.

However, rather than simulating data, one can instead use the solution to the log-linearised version of the DSGE model to analytically compute the population moments of y_t, since the DSGE model specifies the stochastic process for y_t. So by choosing λ, we can scale these moments to be equivalent in magnitude to the (non-standardised) sample moments that would have been obtained through simulation. Given this, we can then formulate the prior for the VAR parameters, $p(\Phi, \Sigma_u|\theta)$, given θ, as $\Sigma_u|\theta \sim IW$ and $\Phi|\Sigma_u, \theta \sim N$, i.e., in an Inverted-Wishart (IW)–Normal (N) form. Note, the parameters of these prior densities are functions of the population moments calculated from the DSGE model.[8] Given that, we also have prior beliefs about the parameters of the DSGE model, $p(\theta)$. The joint prior density of both sets of parameters is then given by:

$$p(\Phi, \Sigma_u, \theta) = p(\Phi, \Sigma_u|\theta) p(\theta). \tag{2}$$

The posterior distribution of the VAR parameters, $p(\Phi, \Sigma_u|Y, \theta)$, is obtained by the likelihood function, which is essentially the combination of the prior with information from the data. Note the likelihood, reflecting the distribution of the innovations (u_t), and the priors for the VAR parameter conjugate, since the former is multivariate normal, while the latter is Inverted-Wishart–Normal. This is particularly helpful, since it allows the posterior to be $\Sigma_u'|\theta, Y \sim IW$ and $\Phi|\Sigma_u, \theta, Y \sim N$,[9] i.e., the posterior follows the same class of distributions as the prior. Finally, by first drawing a θ from the posterior of the DSGE

[5] Note that, we do not explicitly estimate the DSGE model independently, we just use a large weight on λ as in Del Negro et al. (2007), which is akin to estimating the DSGE model on its own.

[6] Intuitively, the DSGE-VAR approach starts from the assumption that a DSGE model may provide useful restrictions for the VAR parameters, in the sense that these restrictions can improve the model's forecasting performance. With the DSGE models at times being an overly simplified structure of the true economy, one does not want to impose these restrictions dogmatically. Instead, the DSGE model is used as prior information in the estimation. As is well known since the work of Theil and Goldberger (1961), one way to incorporate prior information into the estimation is to augment the sample with dummy observations that reflect the prior. This is precisely what is done in the DSGE-VAR estimation: First, dummy observations are simply data generated by the DSGE model, and second, the VAR parameters are estimated using both the actual and the dummy observations, with the weight on the prior determining how much of the data generate from the DSGE model is used in the estimation. The reader is referred to Del Negro and Schorfheide (2003) for further details.

[7] More specifically, the SARB has now adopted an explicit inflation targeting regime, whereby it aims to keep the CPIX inflation rate, where CPIX is defined as Consumer Price Index (CPI) excluding interest rates on mortgage bonds, within the target band of 3% to 6%, using discretionary changes in the Repurchase (Repo) rate as its main policy instrument.

[8] See Eqs. (24) and (25) in Del Negro and Schorfheide (2004) for further details.

[9] We have suppressed the parameters of the posterior distributions. See Eqs. (30) and (31) in Del Negro and Schorfheide (2004) for further details.