Discussion of Bache, Brubakk and Maih
"Estimating monetary policy when the model is misspecified"

Jesper Lindé

Federal Reserve Board

Norges Bank Workshop on Optimal Monetary Policy
November 21-22, 2008
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  - Forecasting performance improved when allowing for misspecification, interest rates and inflation model forecasts close to official Norges Bank forecasts for inflation and the policy rate
Discussion outline

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- Non-petroleum version of the Norwegian economy (e.g. match mainland GDP)
- Can you analyse an economy like Norway without oil in the model? GE-effects of oil?
Sample and set of observed variables

Lower inflation and interest rates after 1993
You use 11 variables to estimate the model. No foreign variables included. Problematic for two reasons:

1. Without the foreign variables included, NEMO can filter out foreign variables to be very different to what they actually are to improve the fit of the model.

2. As I understand it, you also assume that foreign variables are given by univariate AR(1) processes. This assumption is surely strongly rejected by the data.

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- For same reasons, would work with trade balance rather than exports (or take in imports)
Simple rule vs. loss function estimation results

- Specification of simple rule:

\[ r_t^* = \omega_r r_{t-1}^* + (1 - \omega_r) [\omega_\pi \hat{\pi}_t + \omega_y \hat{y}_t + \omega_{rer} \hat{rer}_t] \]  

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- Loss function specification

\[ L_t = \pi_t^2 + \omega_y y_t^2 + \omega_{\Delta r} (r_t^* - r_{t-1}^*)^2 \]

and associated implicit targeting rule

\[ r_t^* = \omega_S S_{t-1} + \omega_\theta \theta_t \]  

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where; \( S \) - vector with state variables (i.e. \( r_{t-1}^* \), Lagrangian multipliers + other states) and \( \theta_t \) - vector with shocks
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- **With large number of unobserved variables in the estimation, this probably gives ITR an advantage over SR**
Use authors’ posterior means to compute residuals in SR (compute $\hat{y}_t$ in SR by HP-filter the GDP series, estimate the constant)
Simple rule vs. loss function estimation results
A simple assessment on role of policy shocks

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Simple rule vs. loss function estimation results
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- Fitted and actual values of SR shown in figure below
- From figure, compute standard deviation of policy shock of about 1.04.

Passing the residuals and the standard deviation to log-likelihood function yields a contribution of about 122 units. Given that difference in favor of LF to SR is 65.7 units, this assumption could be of key importance.
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Fit of the estimated Taylor rule
In Adolfson et al. (2008), marginal likelihood for SR falls by 87.5 units if policy shock is omitted.
Simple rule vs. loss function estimation results
An alternative assessment on the importance of allowing for policy shocks

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- To sum up: Should consider including policy shocks in SR. More fair comparison of SR and LF approaches
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- Figure below from Adolfson et al (2007)
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DSGE-VAR estimation results

DSGE-VAR misspecification

- Your estimated value of $\hat{\lambda} \approx 1$ suggests that misspecification is substantial in both versions of the model.

- Too little persistence in the estimated simple rule, $\hat{\omega} = 0.67$. When estimating simple rule as a single equation (imposing the 1.5 coefficient on inflation), obtain $\hat{\omega} = 0.975$ (see Table below). This alternative parameterization should give rise to more persistence in interest rate forecasts, i.e. explain the difference between pure model and DSGE-VAR forecasts.

- Low estimated value for $\hat{\omega}$ most likely driven by omitted policy shocks.
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Dependent Variable: R\_APR  
Method: Least Squares  
Date: 11/19/08   Time: 12:55  
Sample: 1987Q1 2007Q4  
Included observations: 84  
Convergence achieved after 5 iterations  
R\_APR = C(1)*R\_APR(-1) + (1-C(1))*(1.5*PIE\_APR+4*C(3)*YGAP\_HP  
 +C(4)*RERALT+4.75)  

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>t-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>C(1)</td>
<td>0.974969</td>
<td>0.024951</td>
<td>39.07598</td>
<td>0.0000</td>
</tr>
<tr>
<td>C(3)</td>
<td>1.202010</td>
<td>1.476648</td>
<td>0.814012</td>
<td>0.4180</td>
</tr>
<tr>
<td>C(4)</td>
<td>0.239815</td>
<td>0.577171</td>
<td>0.415501</td>
<td>0.6789</td>
</tr>
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</table>

R-squared 0.955774  Mean dependent var  6.142500
Adjusted R-squared 0.954682  S.D. dependent var  2.835808
S.E. of regression 0.603688  Akaike info criterion  1.863542
Sum squared resid  29.51957  Schwarz criterion  1.950357
Log likelihood -75.26877  Hannan-Quinn criterion  1.898441
Durbin-Watson stat 0.958730
Figure 4: Actual policy rate, Norges Bank’s official forecasts and model forecasts
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Can the DSGE-VAR approximate the forecasting process in Norges Bank?

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  - Even if forecasts for all variables about the same, could be the case Norges Bank have used judgment in their official forecasts, but have held firm belief in the propagation mechanism in NEMO.
- Forecasts from the DSGE-VAR(\(\lambda\)) are not optimal efficient forecasts according to NEMO.
  - How conduct optimal monetary policy in the DSGE-VAR model(\(\hat{\lambda}\))?