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
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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

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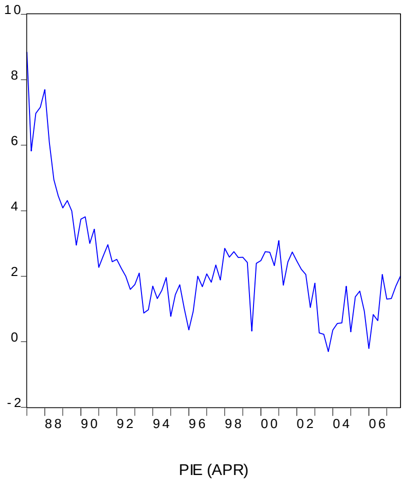
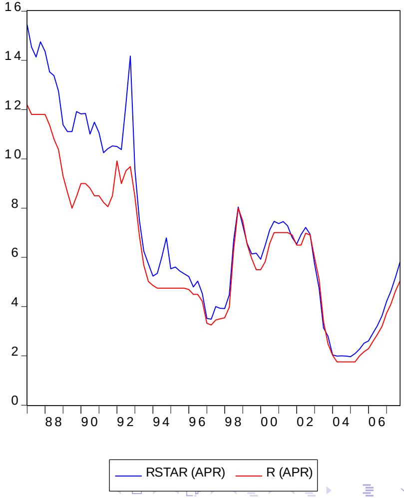
- Non-petroleum version of the Norwegian economy (e.g. match mainland GDP)
  - Can you analyse an economy like Norway without oil in the model? GE-effects of oil?

Sample and set of observed variables

Lower inflation and interest rates after 1993





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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:

$$r_t^* = \omega_r r_{t-1}^* + (1 - \omega_r) \left[\omega_\pi \hat{\pi}_t + \omega_y \hat{y}_t + \omega_{rer} \widehat{rer}_t \right] \qquad \text{(SR)}$$

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$$\mathrm{L}_t = \pi_t^2 + \omega_y y_t^2 + \omega_{\Delta r}\left(r_t^* - r_{t-1}^*\right)^2$$

and associated implicit targeting rule

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- With large number of unobserved variables in the estimation, this probably gives ITR an advantage over SR

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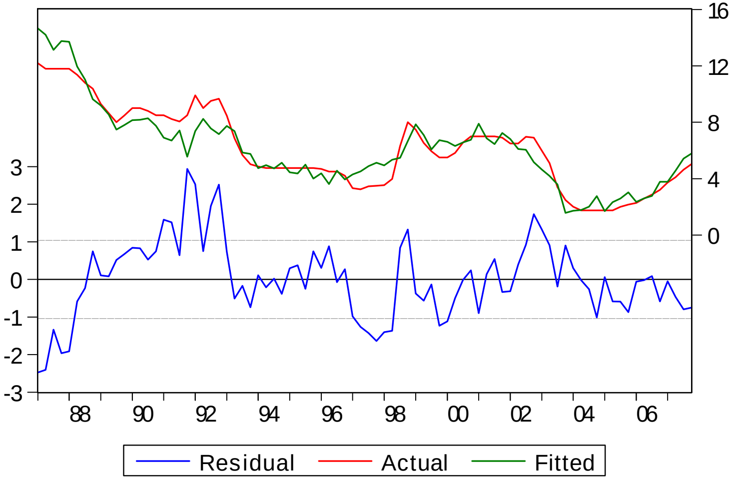
  - Given that difference in favor of LF to SR is 65.7 units, this assumption could be of key importance

Simple rule vs. loss function estimation results

Fit of the estimated Taylor rule



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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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DSGE–VAR approximation

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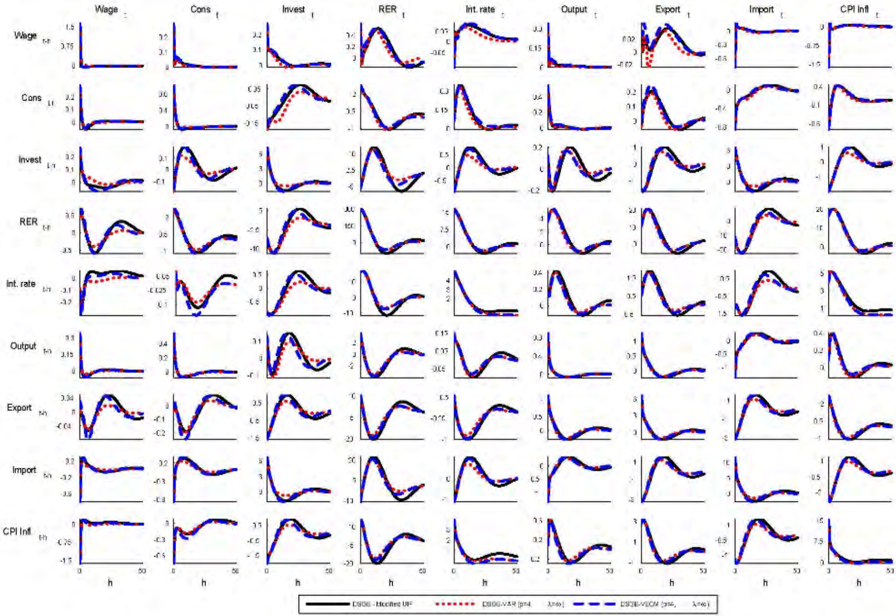
  - Figure below from Adolfson et al (2007)



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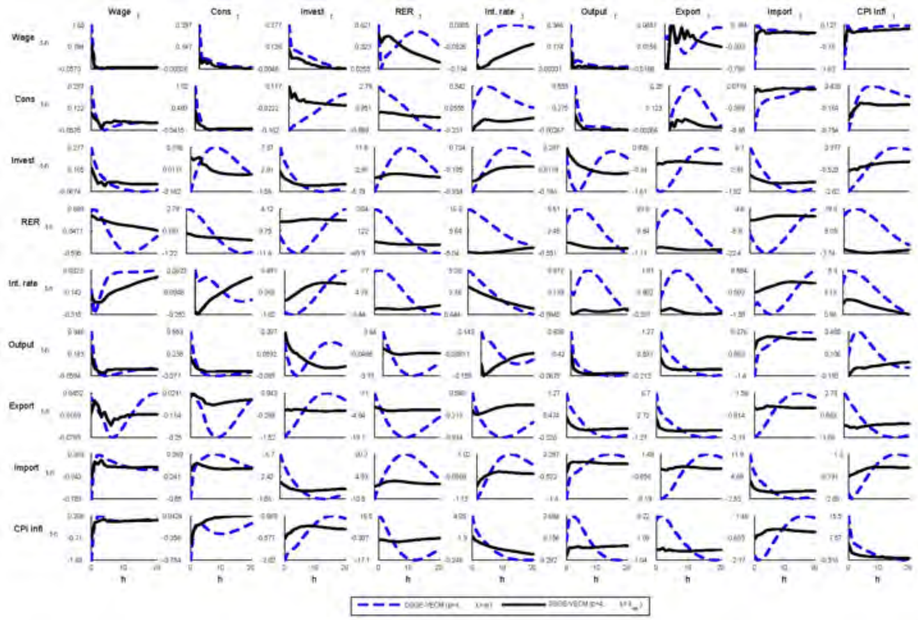
  - See figure below from Adolfson et al (2007), $\hat{\lambda} = 5.5$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  - Low estimated value for ω_r most likely driven by omitted policy shocks

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)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	0.974969	0.024951	39.07598	0.0000
C(3)	1.202010	1.476648	0.814012	0.4180
C(4)	0.239815	0.577171	0.415501	0.6789

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 criter.	1.898441
Durbin-Watson stat	0.958730		

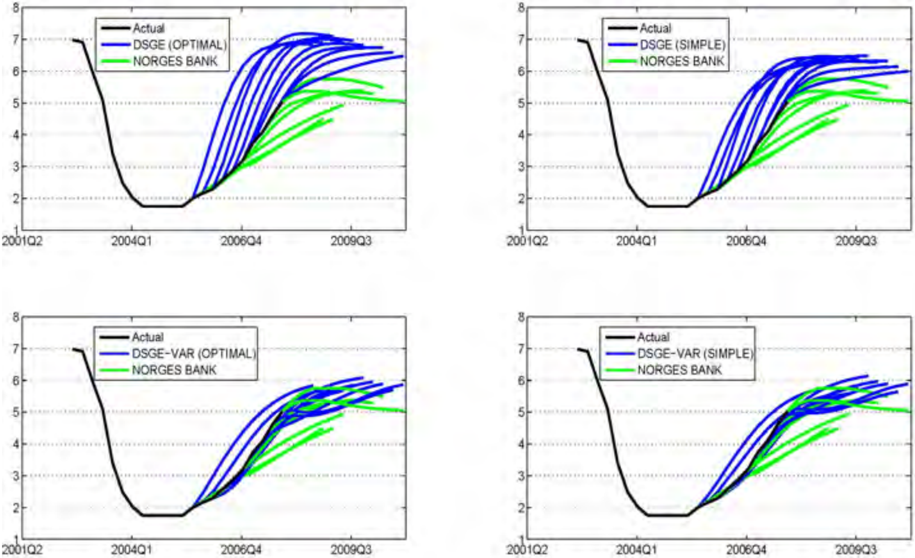

Figure 4: Actual policy rate, Norges Bank's official forecasts and model forecasts

DSGE-VAR and Norges Bank forecasts

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- Forecasts from the DSGE-VAR(λ) are not optimal efficient forecasts according to NEMO

DSGE-VAR and Norges Bank forecasts

Can the DSGE-VAR approximate the forecasting process in Norges Bank?

- A striking finding in the paper is that the DSGE-VAR($\hat{\lambda}$) forecasts for inflation and the policy rate are very similar to the official forecasts published by Norges Bank. Authors interpret this to imply that the DSGE-VAR is the "mental model" of Norges Bank
  - The DSGE-VAR($\hat{\lambda}$) offsets the propagation mechanism in NEMO
- However, in order to provide firm evidence for this claim, must also compare forecasts for other key variables as well (e.g. nominal wages, labor productivity growth)
  - 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(λ) are not optimal efficient forecasts according to NEMO
  - How conduct optimal monetary policy in the DSGE-VAR model($\hat{\lambda}$)?