Introduction to Bayesian Estimation of DSGF Models

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Introduction

- DSGE models are the workhorse models in Macroeconomics
 - Real Business Cycle Models
 - New Keynesian Models
- Two possible approaches to obtaining meaningful results
 - Calibration techniques
 - Econometric estimation procedures

<u>Goal</u>: Cover basic Bayesian techniques and their applications to a medium scale New-Keynesian model

Introduction

- Why should you use Bayesian techniques?
 - 1) Medium between calibration and MLE
 - 2) Straigtforward model comparison
 - 3) Likelihood function is highly nonlinear
 - 4) Asymptotic theory hold in computation space
- It all starts here:

$$P(\vartheta|\mathbf{X}) = \underbrace{\frac{\int\limits_{\vartheta}^{likelihood} prior}{\int\limits_{\vartheta} p(\mathbf{X}|\vartheta) p(\vartheta) d\vartheta}}_{marginal}$$

Model

NK Model: Households

- Unit measure of households who discount the future at rate β
- Subject to "habit stock", $\frac{C_t}{A_t}$, supply labor, H_t
- Pays lump taxes, T_t , and hold real money balance, $\frac{M_t}{P_t}$
- Access to government bonds, B_t, and state-contingent securities, SC_t
- Receive residual firm profits, D_t

NK Model: Households

• Representative agent's problem:

$$\max \ \mathbb{E}_t \left[\sum_{s=0}^{\infty} \beta^s \left(\frac{(C_{t+s}/A_{t+s})^{1-\tau} - 1}{1-\tau} + \ln \left(\frac{M_{t+s}}{P_{t+s}} \right) - H_{t+s} \right) \right]$$

subject to the B.C.

$$P_t C_t + B_t + M_t + T_t = P_t W_t H_t \dots + P_t S C_t + R_{t-1} B_{t-1} + M_{t-1} + P_t D_t$$

NK Model: Final Goods

- Final goods market is perfectly competitive
- CES production aggregates unit measure of intermediate goods

$$Y_t = \left(\int_0^1 Y_t(j)^{1-\nu} dj\right)^{\frac{1}{1-\nu}}$$

• Firms problem,

$$\max \ \Pi_t = P_t \left(\int_0^1 Y_t(j)^{1-\nu} dj \right)^{\frac{1}{1-\nu}} - \int_0^1 P_t(j) Y_t(j) dj$$

NK Model: Intermediate Goods

- Intermediate goods market is monopolistically competitive
- Labor market is frictionless and perfectly competitive
- Linear technology subject to productivity shocks,

$$Y_t(j) = A_t N_t(j)$$

• Quadratic price adjustment cost,

$$AC_t(j) = \frac{\phi}{2} \left(\frac{P_t(j)}{P_{t-1}(j)} - \pi \right)^2 Y_t(j)$$

• Firms problem,

$$\max \mathbb{E}_t \left[\sum_{s=0}^{\infty} \beta^s Q_{t+s|t} \left(\frac{P_{t+s}(j)}{P_{t+s}} Y_{t+s}(j) - W_{t+s} N_{t+s}(j) - AC_{t+s}(j) \right) \right]$$

NK Model: Government

Monetary policy subject to interest feedback rule

$$\ln R_t = (1 - \rho_R) \ln R_t^* + \rho_R \ln R_{t-1} + \epsilon_{R,t}$$

- Target nominal rate, R_t^* , given by
 - 1) Steady-state real interest rate, r
 - 2) Gross and target inflation rate, π^*
 - 3) Level-output gap due to nominal rigidities

$$\ln R_t^* = \ln r + (1 - \psi_1) \ln \pi^* + \psi_1 \ln \pi_t + \psi_2 \ln \left(\frac{Y_t}{Y_t^*}\right)$$

• Fiscal policy given by government B.C.,

$$P_t G_t + R_{t-1} B_{t-1} + M_{t-1} = T_t + B_t + M_t$$

NK Model: Exogenous Processes

Aggregate productivity given by random walk with drift,

$$\ln A_t = \ln \gamma + \ln A_{t-1} + \ln z_t, \quad \ln z_t = \rho_z \ln z_{t-1} + \epsilon_{z,t}$$

• Define $g_t = \frac{1}{1-\zeta_t}$ where ζ_t is fraction of Y_t purchased by government,

$$\ln g_t = \left(1 - \rho_g\right) \ln g + \rho_g \ln g_{t-1} + \epsilon_{g,t}$$

Shocks are mean zero and uncorrelated,

$$\begin{bmatrix} \epsilon_{R,t} \\ \epsilon_{z,t} \\ \epsilon_{g,t} \end{bmatrix} \sim \mathcal{N} \left(\begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \sigma_R^2 & 0 & 0 \\ 0 & \sigma_z^2 & 0 \\ 0 & 0 & \sigma_g^2 \end{bmatrix} \right)$$

Likelihood Function

Solving the Model

- Use the following steps to solve the model:
 - 1) Solve for equilibrium conditions
 - 2) Find non-stochastic steady state by setting $\sigma = 0$
 - 3) Transform model variables by $x_t = \frac{X_t}{A_t}$
 - 4) Rewrite equilibrium conditions as deviations from s.s.:

$$\hat{x}_t = \ln\left(\frac{x_t}{x_{ss}}\right)$$

5) Find 1st order approximation about steady state

Linear Rational Expectations System

Linearized equilibrium conditions,

$$egin{aligned} \hat{y}_t &= \mathbb{E}_t(\hat{y}_{t+1}) - rac{1}{ au} \left(\hat{R}_t - \mathbb{E}_t(\hat{\pi}_{t+1}) - \overbrace{\mathbb{E}_t(\hat{z}_{t+1})}^{
ho_z \hat{z}_t}
ight) + \hat{g}_t - \overbrace{\mathbb{E}_t(\hat{g}_{t+1})}^{
ho_g \hat{g}_t} \ \hat{\pi}_t &= eta \mathbb{E}_t(\hat{\pi}_{t+1}) + \underbrace{ au}_{ au} rac{1 -
u}{
u \pi^2 \phi} (\hat{y}_t - \hat{g}_t) \end{aligned}$$

$$\begin{split} \hat{R}_t &= \rho_R \hat{R}_{t-1} + (1 - \rho_R) \psi_1 \hat{\pi}_t + (1 - \rho_r) \psi_2 (\hat{y}_t - \hat{g}_t) + \epsilon_{R,t} \\ \hat{g}_t &= \rho_g \hat{g}_{t-1} + \epsilon_{g,t} \\ \hat{z}_t &= \rho_z \hat{z}_{t-1} + \epsilon_{z,t} \end{split}$$

Quasi-Schur Decomposition

- Need to impose the transveraslity condition
- Define the following

1)
$$s_t = [\hat{y}_t, \hat{\pi}_t, \hat{R}_t, \hat{y}_{t-1}, \hat{g}_t, \hat{z}_t, \mathbb{E}_t(\hat{y}_{t+1}), \mathbb{E}_t(\hat{\pi}_t)]'$$

- 2) $\epsilon_t = [\epsilon_{z,t}, \epsilon_{g,t}, \epsilon_{R,t}]'$
- 3) $\eta_t = [\hat{y}_t \mathbb{E}_{t-1}(\hat{y}_t), \hat{\pi}_t \mathbb{E}_{t-1}(\hat{\pi}_t)]'$

$$\Rightarrow \Gamma_0 s_t = \Gamma_1 s_{t-1} + \Psi \epsilon_t + \Pi \eta_t$$

Apply Quasi-Schur decomposition,

$$\Gamma_0 = Q'\Omega Z'$$
 $\Gamma_1 = Q'\Lambda Z'$

where, Λ and Ω are triangular and Q'Q = Z'Z = I

Quasi-Schur Decomposition

- Generalized eigenvalues of Γ_0 and Γ_1 are given by $\frac{\lambda_{ii}}{\omega_{ii}}$
- BPremultiply system by Q, define $w_t = Z's_t$, and substitute for Γ_0 , Γ_1 :

$$\Omega w_t = \Lambda w_{t-1} + Q(\Psi \epsilon_t + \Pi \eta_t)$$

- Partition system into nonexplosive block (1) and explosive block (2)
 - 1) Need $w_{2,0} = 0 \ \forall$ structural shocks
 - 2) Need shocks and expectation errors of (2) to cancel $\forall t$

Quasi-Schur Decomposition

• Solve for $w_{2,t-1}$ and iterate explosive block forward, $w_{2,t-1} = \lim_{T \to \infty} (\Lambda_2^{-1} \Omega_2)^T w_{2,t+T} - \sum_{i=1}^{\infty} \Lambda_2^{-i} Q_2 (\Psi \epsilon_{t+i} + \Pi \eta_{t+i})$

• Diagonal elements of $\Lambda_2^{-1}\Omega_2$ are inverse e-vals, $\frac{\omega_{ii}}{\lambda_{ii}} < 1$

$$\Rightarrow \lim_{T\to\infty} \left(\frac{w_{nn}}{\lambda_{nn}}\right)^T = 0 \Rightarrow w_{2,t}^{(n)} = 0 \Rightarrow w_{2,t}^{(n-1)} = 0 \dots$$

Sufficient condition for req. 2 is

$$\eta_t = -(Q_2\Pi)^{-1}Q_2\Psi\epsilon_t$$

State-Space Form

• Substitute expectation errors and solve for s_t

$$s_t = \Phi_1 s_{t-1} + \Phi_2 \epsilon_t$$

Define observer equation

$$\zeta_t = \Upsilon_1 + \Upsilon_t s_t + u_t$$

- Avoid stochastic singularity by
 - 1) Limiting number of observables
 - 2) Adding measurement errors

State-Space Form

- Define the following set of observables:
 - 1) Quarterly GDP growth rate

$$GR_t = \gamma^Q + 100(\hat{y}_t - \hat{y}_{t-1} + \hat{z}_t)$$

2) Annualized quarterly inflation rate

$$INF_t = \pi^A + 400\hat{\pi}_t$$

3) Annualized nominal interest rate

$$INT_t = \pi^A + r^A + 4\gamma^Q + 400\hat{R}_t$$

State-space model implies joint likelihood function

$$p(\zeta_{1:t}, s_{1:t}|\theta) = \prod_{t=1}^{l} p(\zeta_{t}|s_{t}, \theta) p(s_{t}|s_{t-1}, \theta)$$

Kalman-Filter

- Bayesian (and frequentist) inference can only be done using observables
- Integrate out unobservables using Linear (Kalman) Filter
 - Requires normally distributed shocks
 - Initiate at stationary distribution
- Stept to Kalman-Filter:
 - 1) Predict distribution of unobservables
 - 2) Obtain distribution of unobservables using prediction
 - 3) Update prediction using distribution of observables

Likelihood Function

Algorithm

Find likelihood function using collection of step 2,

$$p(\zeta|\theta) = \prod_{t=1}^{l} p(\zeta_t|\zeta_{1:t-1},\theta)$$

Prior

Prior Specification

Conduct literature review of parameter micro-level estimates

 Partition data into pre- & post-sample and calculate statistics using pre-sample

- Calculate statistics of interest using joint-prior
 - 1) Cross-correlations
 - 2) Impulse response functions

Prior Specification

• Priors taken from Lubik and Schorfheide (2004)

Prior Distributions

Param Domain		Dist	Mean StnDev	
ρ_{g}	[0, 1]	Uniform	0.5	0.29
$ ho_{z}$	[0, 1]	Uniform	0.5	0.29
κ	[0, 1]	Uniform	0.5	0.29
$ ho_R$	[0, 1]	Uniform	0.5	0.29
r^A	\mathbb{R}^+	Gamma	0.5	0.5
π^{A}	\mathbb{R}^+	Gamma	7.0	2.0
au	\mathbb{R}^+	Gamma	2.0	0.5
ψ_1	\mathbb{R}^+	Gamma	1.5	0.24
ψ_{2}	\mathbb{R}^+	Gamma	0.50	0.25
σ_R	\mathbb{R}^+	InvGamma	0.40	4.0
$\sigma_{\it G}$	\mathbb{R}^+	InvGamma	1.0	4.0
σ_{z}	\mathbb{R}^+	InvGamma	0.50	4.0
γ^{A}	\mathbb{R}	Normal	0.40	0.20

Posterior

Metropolis-Hastings

Recall Baye's Law,

$$P(\vartheta|\mathbf{X}) = \frac{p(\mathbf{X}|\vartheta)p(\vartheta)}{\int\limits_{\vartheta} p(\mathbf{X}|\vartheta)p(\vartheta)d\vartheta}$$

- Joint distribution may not have closed form integral
 - No analytical solution
- Conditional distributions may take no known functional form
 - No Gibbs sampling
- Turn to Metropolis-Hastings algorithms

Metrpolois-Hastings

- Draws samples from P(x) using only f(x) where $P(x) \propto f(x)$ and proposal distribution
 - Set $P(x) = P(\vartheta | X)$
 - Set $f(x) = p(X|\vartheta)p(\vartheta)$
- Numerous algorithms with different proposal distributions, $q(\vartheta^*|\vartheta^{(s-1)})$

Algorithm

- 1) Choose $\vartheta^{(0)}$ mostly arbitrarily
- 2) Draw proposal from $q(\vartheta^*|\vartheta^{(s-1)})$
- 3) Set $\vartheta^{(s)} = \vartheta^*$ with probabilty $\alpha(\vartheta^*, \vartheta^{(s-1)}) = \min\{\frac{\rho(\vartheta^*|\mathbf{X})/q(\vartheta^*|\vartheta^{(s-1)})}{\rho(\vartheta^{(s-1)}|\mathbf{X})/q(\vartheta^{(s-1)}|\vartheta^*)}, 1\}$
- 4) Repeat until convergence of means

Matrpolis-Hastings

- Unclear direction for $\vartheta^{(0)}$ to move \Rightarrow use Random Walk-MH
- Proposal distribution given by,

$$egin{aligned} artheta^* &= artheta^{(s-1)} + z &\Leftrightarrow & q(artheta^* | artheta^{(s-1)}) &= \mathcal{N}(artheta^{(s-1)}, c^2 \hat{\Sigma}) \ \\ &\Rightarrow & lpha(artheta^*, artheta^{(s-1)}) &= \min\{rac{p(artheta^* | oldsymbol{X})}{p(artheta^{(s-1)} | oldsymbol{X})}, 1\} \end{aligned}$$

- Many ways to choose $\hat{\Sigma}$
 - 1) Inverse Hessian of log-posterior at mode
 - 2) Covariance matrix of pre-estimation RWMH
- Set tuning constnat, c, to get 20%-40% acceptance

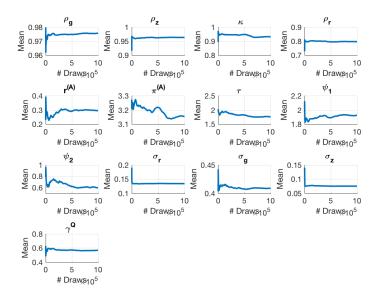
Results: Algorithm

• 10,000 iteration pre-estimation RWMH to obtion $\hat{\Sigma}$ using $\Sigma = I$

- Collect FRED data from 1983-2003
 - 1) GR_t from real GDP and adult civilian pop.
 - 2) INF_t from CPI for all urban goods
 - 3) INT_t from effective federal funds rate

1,000,000 posterior samples with 500,000 burn in

Results: Convergence



Results: Posterior

