Bayesian Estimation

Bayesian Estimation in Dynare

Tools for Macroeconomists: The essentials

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Bayesian Estimation in Dynare

Preliminaries

- setup is the same as with ML estimation
- always a good idea to solve model first
- some parameter values are likely to remain calibrated

Bayesian estimation in Dynare: initialization

- initialize as usual

```
var c, k, z, y;
varexo e;
parameters beta, rho, alpha, nu, delta, sigma;
```

- set parameter values that are not estimated

```
alpha = 0.36;
rho = 0.95;
beta = 0.99;
nu = 1;
delta = 0.025;
```

Bayesian Estimation in Dynare

Priors, Steady State and Estimation

Bayesian estimation in Dynare: setting it up

- after model part, and specification of steady state
- tell Dynare which parameters he should estimate

```
estimated_params;
stderr e, inv_gamma_pdf, 0.01, inf;
end;
```

- the above tells Dynare to
  - estimate σ, the st. error of the productivity disturbance
  - the prior distribution is an inverted gamma
  - the prior mean is 0.01 and the prior st. error is ∞

Bayesian estimation in Dynare: steady state

- steady state calculated for many different values of Ψ!
- solve for the steady state yourself (linearizing makes it easier)
- give the exact steady state to Dynare for the initial values
- option to provide own function that calculates steady state!
    - `modfilename_steadystate.m` or
    - `steady_state_model;` block

Bayesian estimation in Dynare: estimation

- then also tell Dynare which are the observable variables

```
varobs y;
estimation(options);
```

- options include
  - specify data file for estimation: `datafile=data`
  - number of MH sequences: `mh_nblocks`
  - number of MH replications: `mh_replic`
  - parameter of stand-in distribution variance (c): `mh_jscale`
  - variance of initial draw: `mh_init_scale`
  - first observation (default first): `first_obs`
  - sample size (default all): `nobs`
  - many more!

Bayesian Estimation in Dynare

Decompositions

Bayesian estimation in Dynare: decomposition

- decompose endogenous variables into contribution of shocks
- possible also after `stoch_simul`

```
shock_decomposition(options) variables;
```

- options include e.g. `parameter_set`
  - use calibrated values: `=calibration`
  - use prior/posterior mode: `=prior_mode`/`=posterior_mode`
- variables specifies for which variables to run the decomposition

Bayesian estimation in Dynare: output

RESULTS FROM POSTERIOR MAXIMIZATION:

- most important is the mode
- other stuff based on normality assumptions (typically violated)

when Dynare gets to MCMC part it shows:

- in which MCMC sequence you are
- which fraction has been completed
- **acceptance rate**: adjust `mh_jscale` appropriately
  - remember that low acceptance rate
  - $\rightarrow$ algorithm travels through a larger part of Ψ domain

Bayesian estimation in Dynare: plots

- priors
- MCMC diagnostics
- prior and posterior densities
- shocks implied at the mode
- observables and corresponding implied values

Bayesian Estimation in Dynare

Example Code

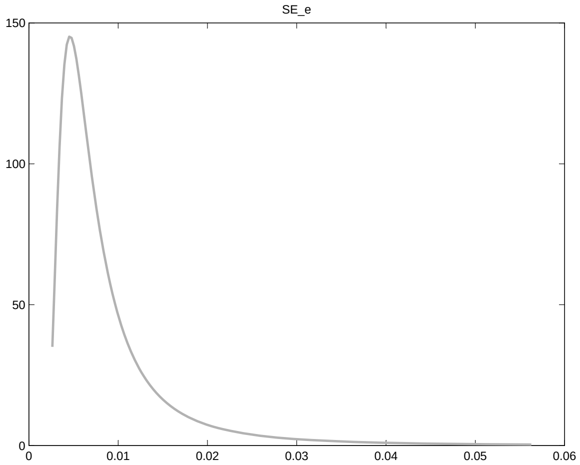
Estimating the neoclassical growth model

- use neoclassical growth model as data generating process
- 265 observations of output
- use Bayesian estimation to estimate
  - σ
  - σ, ρ, δ, α

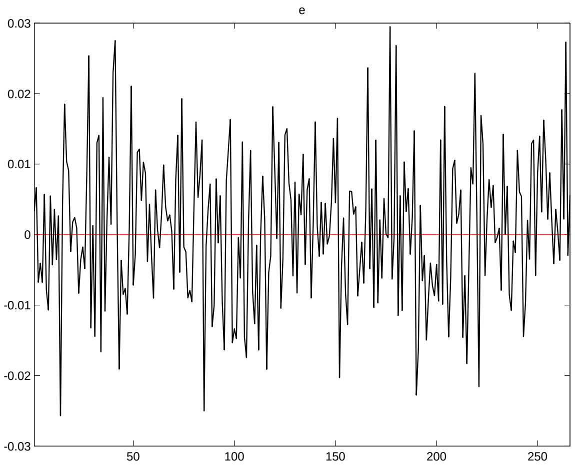
Easy case:

```
estimated_params;
stderr e, inv_gamma_pdf, 0.01, inf;
end;
varobs y; estimation(datafile=y,mh_nblocks=1,mh_replic=10000,
          mh_jscale=3,mh_init_scale=12) c, k, y;
```

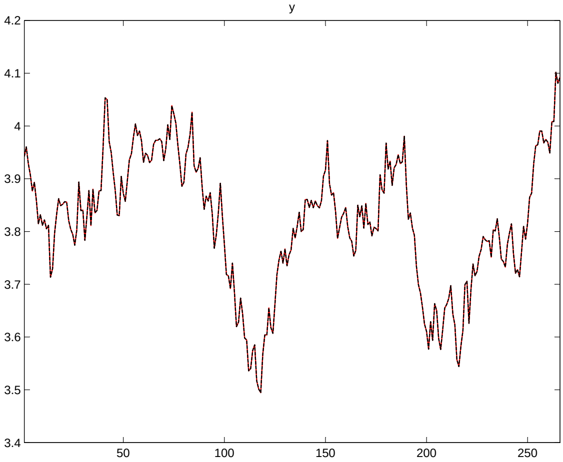
MCMC PRIOR PLOTS-EASY CASE



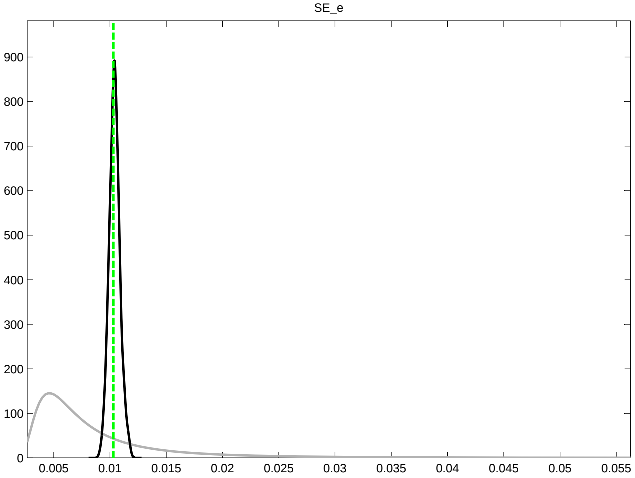
Shocks-easy case



Observables and implied values-easy case



Posterior density plots-easy case



Printed results - easy case

Posterior mode:

`0.0103 (0.0004)`

Average acceptance rate:

`37.7%`

Diagnostic statistics (Geweke):
p-values on equality of means in sub-samples

`0.037 (no taper) 0.33 (4% taper) 0.38 (8% taper) etc.`

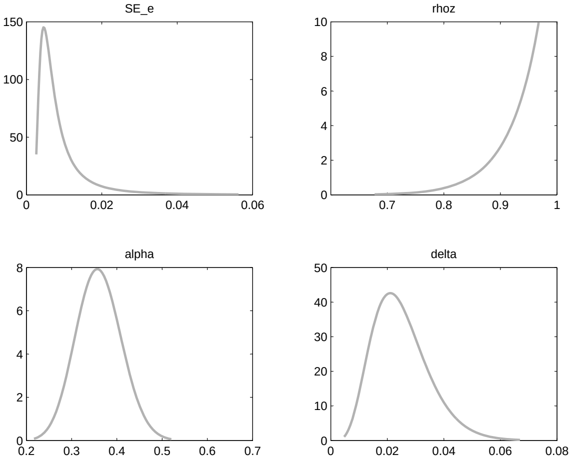
Posterior mean and HPD interval:

`0.0104 (0.0096 - 0.0111)`

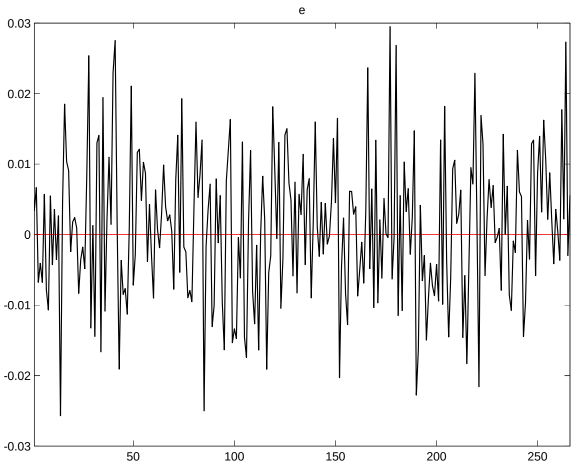
Tough case:

```
estimated_params;
stderr e, inv_gamma_pdf, 0.01, inf;
ρ, beta_pdf, 0.95, 0.05;
α, beta_pdf, 0.36, 0.05;
δ, beta_pdf, 0.025, 0.01;
end;
varobs y; estimation(datafile=y,mh_nblocks=1,mh_replic=10000,
          mh_jscale=1,mh_init_scale=12) c, k, y;
```

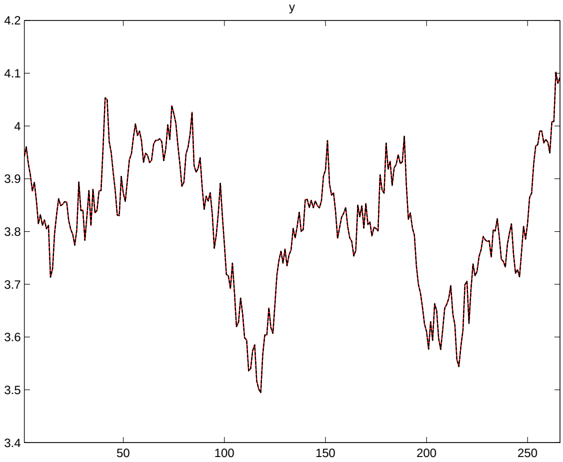
MCMC prior plots-tough case



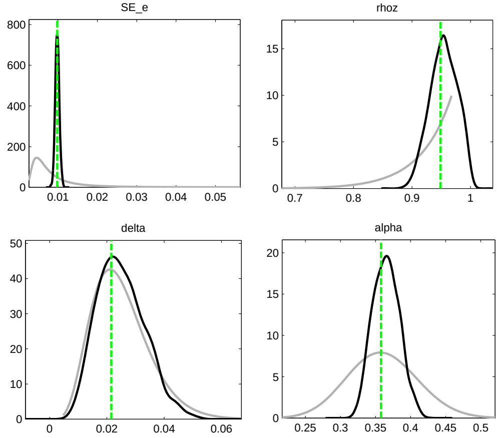
Shocks-tough case



Observables and implied values-tough case



Posterior density plots-tough case



Printed results - easy case

Posterior mode:

σ `0.0098 (0.0005)` ρ `0.9488 (0.0228)`

α `0.3578 (0.0205)` δ `0.0215 (0.0087)`

Average acceptance rate:

`34.5%`

Diagnostic statistics (Geweke):

p-values on equality of means in sub-samples

σ `0.73 (no taper) 0.93 (4% taper) 0.94 (8% taper)`

ρ `0.00 (no taper) 0.10(4% taper) 0.15 (8% taper)`

α `0.00 (no taper) 0.13 (4% taper) 0.14 (8% taper)`

δ `0.00 (no taper) 0.09 (4% taper) 0.10 (8% taper)`

Printed results - easy case

Posterior mean and HPD interval:

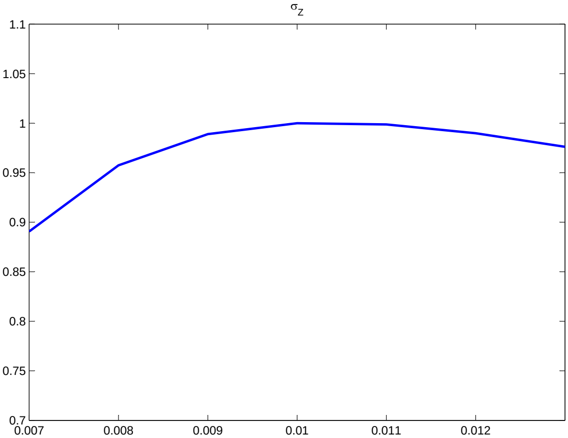
σ `0.0098 (0.0090 - 0.0106)`

ρ `0.9538 (0.9184 - .9922)`

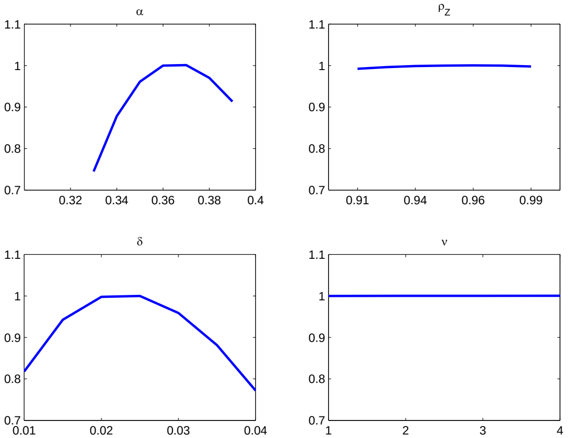
α `0.3649 (0.3338 - 0.3924)`

δ `0.0249 (0.0132 - 0.0385)`

Likelihood profiles



Likelihood profiles



Bayesian Estimation in Dynare

Taking Stock

Taking stock

Estimating DSGE models with Bayesian Methods in Dynare

- same structure of program as when solving a model
  - beware of same pitfalls (timing, notation)
- estimation command straightforward
  - specify data, which variables are observed and initial values
  - instead of lower and upper bounds (as is the case for ML), specify priors


That's all Folks!