Bayesian Dynamic Stochastic General Equilibrium models in Stata 17

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Bayesian econometrics in Stata

- Stata 17 introduces Bayesian estimation of a variety of time–series and panel–data econometric models
  - `bayes: dsge`
  - `bayes: dsgenl`
  - `bayes: var`
  - `bayesirf`
  - `bayesfcast`
  - `bayes: xt`

Outline

- DSGE models, `dsge`, and `bayes: dsge`
- AR(1) model
- Linear New Keynesian model
- Nonlinear stochastic growth model

DSGE models

- A DSGE model is a system of equations that describes an economy.
- A model consists of three kinds of variables:
  - Control variables, whose values are determined by the system of equations each period
  - State variables, which are fixed at the beginning of any given period but whose laws of motion are part of the system of equations
  - Stochastic shocks, which drive the system
- DSGE models come from economic theory. Theories are forward-looking, so equations are forward-looking.
- Models are used for policy analysis: explore different policy alternatives or how different parameter values affect model outcomes

An example model

- Suppose we wished to model the effect of monetary policy on macroeconomic variables
- We model relationships among output, inflation, and the interest rate
- These variables are linked to state variables representing monetary shocks, and perhaps other factors
- State variables, in turn, are driven by shocks

An example model

- The following system of equations is a DSGE model:

$$
\begin{aligned}
x_t &= E_t x_{t+1} - (r_t - E_t \pi_{t+1} - z_t) && \text{(IS)} \\
\pi_t &= \beta E_t \pi_{t+1} + \kappa x_t && \text{(Phillips Curve)} \\
r_t &= \frac{1}{\beta} \pi_t + w_t && \text{(Taylor Rule)} \\
w_{t+1} &= \rho_w w_t + e_{t+1} \\
z_{t+1} &= \rho_z z_t + \varepsilon_{t+1}
\end{aligned}
$$

- Control variables: (x_t, π_t, r_t)
- State variables: (w_t, z_t)
- Stochastic shock: (e_t, ε_t)
- Parameters: $(\kappa, \beta, \rho_w, \rho_z, \sigma_e^2, \sigma_\varepsilon^2)'$

DSGE models in Stata

- Model:

$$x_t = E_t x_{t+1} - (r_t - E_t \pi_{t+1} - z_t) \quad \text{(IS)}$$

$$\pi_t = \beta E_t \pi_{t+1} + \kappa x_t \quad \text{(Phillips Curve)}$$

$$r_t = \frac{1}{\beta} \pi_t + w_t \quad \text{(Taylor Rule)}$$

$$w_{t+1} = \rho_w w_t + e_{t+1}$$

$$z_{t+1} = \rho_z z_t + \varepsilon_{t+1}$$

- In Stata: `dsge` *(model_equations)*

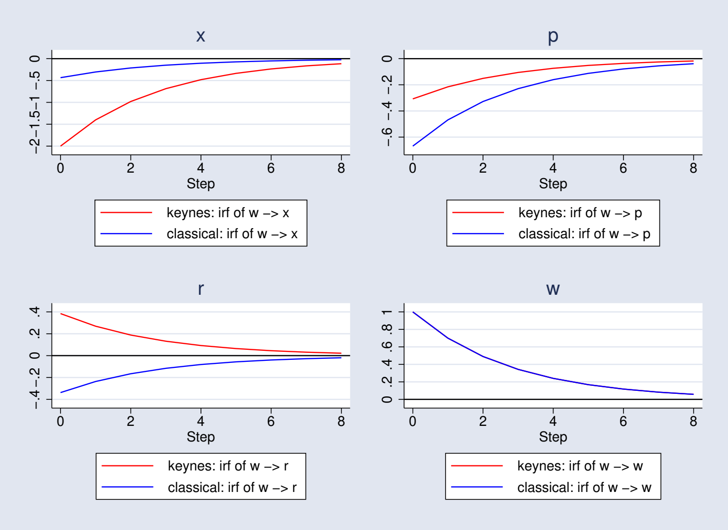
```
. dsge  (x   = F.x - (r - F.p - z)     , unobserved )    ///
        (p   = {beta}*F.p + {kappa}*x               )    ///
        (r   = (1/{beta})*p + w                     )    ///
        (F.z = {rhoz}*z                 , state      )    ///
        (F.w = {rhow}*w                 , state      )
```

Two views on the impact of monetary shocks

```
. quietly webuse usmacro2
. matrix param1 =           (0.1, 0.5, 0.9, 0.7)
. matrix colnames param1 = kappa beta rhoz rhow
. matrix param2 =           (1, 0.5, 0.9, 0.7)
. matrix colnames param2 = kappa beta rhoz rhow
.
. quietly irf set dsge_irf.irf, replace
.
. quietly dsge (x   = F.x - (r - F.p - z)     , unobserved )    ///
>              (p   = {beta}*F.p + {kappa}*x               )    ///
>              (r   = (1/{beta})*p + w                     )    ///
>              (F.z = {rhoz}*z                , state      )    ///
>              (F.w = {rhow}*w                , state      ) ,  ///
>              from(param1) solve
. quietly irf create keynes
.
. quietly dsge (x   = F.x - (r - F.p - z)     , unobserved )    ///
>              (p   = {beta}*F.p + {kappa}*x               )    ///
>              (r   = (1/{beta})*p + w                     )    ///
>              (F.z = {rhoz}*z                , state      )    ///
>              (F.w = {rhow}*w                , state      ) ,  ///
>              from(param2) solve
. quietly irf create classical
```

Two views on the impact of monetary shocks

Impulse responses



Two views on the impact of monetary shocks

Maximum likelihood estimation

```
. dsge (x   = F.x - (r - F.p - z)    , unobserved )         ///
>      (p   = {beta}*F.p + {kappa}*x              )         ///
>      (r   = (1/{beta})*p + w                    )         ///
>      (F.z = {rhoz}*z                , state     )         ///
>      (F.w = {rhow}*w                , state     ) , nolog
```

DSGE model

Sample: 1955q1 thru 2015q4   Number of obs = 244
Log likelihood = -753.57131

	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
/structural						
beta	.5146664	.0783491	6.57	0.000	.3611051	.6682278
kappa	.1659059	.0474074	3.50	0.000	.0729891	.2588226
rhoz	.9545256	.0186424	51.20	0.000	.9179872	.991064
rhow	.7005484	.0452604	15.48	0.000	.6118396	.7892572
sd(e.z)	.6211222	.1015082			.4221699	.8200745
sd(e.w)	2.318207	.3047457			1.720916	2.915497

Bayesian DSGE models

- Estimation of DSGE models has shifted towards the Bayesian approach in the past 15 years
- Substantive:
  - Priors reflect genuine prior beliefs about the distribution of parameter values
  - Priors allow the incorporation of other evidence that is hard to incorporate into the likelihood, e.g. micro-evidence on price adjustment
- Technical:
  - Mapping from structural parameters to solution matrices is highly nonlinear, and identification issues are pervasive
  - Priors can aid in isolating identification problems
  - Priors useful for imposing bounds on parameters

Bayesian analysis and the bayes prefix

- The `bayes:` prefix allows for Bayesian estimation of likelihood-based models
- Just attach `bayes:` to the existing Stata command
  - `bayes: regress y x`
  - default priors provided (can be overwritten)
- For DSGE models:
  - `bayes, prior(`*prior_spec*`): dsge (`*model_equations*`)`
  - some priors are required

Outline

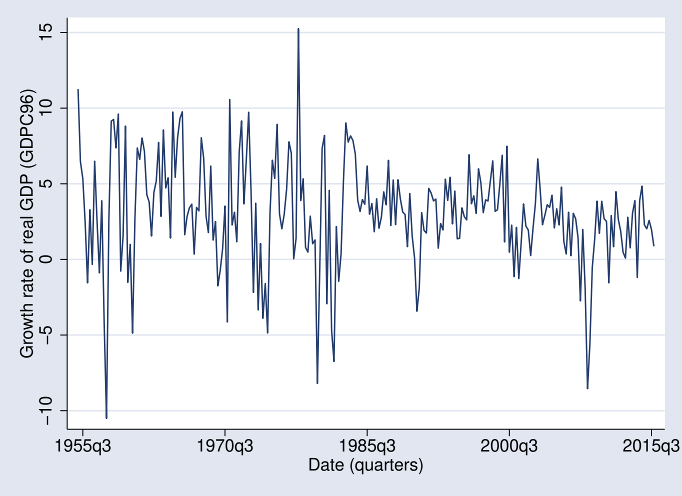
- DSGE models, `dsge`, and `bayes: dsge`
- AR(1) model
- Linear New Keynesian model
- Nonlinear stochastic growth model

US macro data

```
. webuse usmacro2
(Federal Reserve Economic Data - St. Louis Fed, 2017-01-15)

. describe

Contains data from https://www.stata-press.com/data/r17/usmacro2.dta
 Observations:           244                  Federal Reserve Economic Data -
                                                St. Louis Fed, 2017-01-15
    Variables:            11                  1 May 2020 17:52
                                              (_dta has notes)
-------------------------------------------------------------------------------
Variable      Storage   Display    Value
    name         type    format    label      Variable label
-------------------------------------------------------------------------------
daten           int     %td                   Numeric (daily) date
year            int     %9.0g                 Year
quarter         byte    %9.0g                 Quarter
dateq           int     %tq                   Date (quarters)
y               double  %10.0g                Growth rate of real GDP (GDPC96)
p               double  %10.0g                Growth rate of prices (GDPDEF)
r               double  %10.0g                Federal funds rate (FEDFUNDS)
c               double  %10.0g                Growth rate of consumption
                                                (PCECC96)
n               double  %10.0g                Growth rate of hours worked
                                                (HOANBS)
i               double  %10.0g                Corporate bond interest rate
                                                (AAA)
e               double  %10.0g                Percentage change in US exchange
                                                rate (TWEXBMTH)
-------------------------------------------------------------------------------

Sorted by: dateq
```

GDP growth rate

```
. tsline y
```



An AR(1) model

Model

- Model:

$$y_t = \rho y_{t-1} + u_t$$

- State-space formulation:

$$\begin{aligned} y_t &= z_t && \text{(Observation equation)} \\ z_t &= \rho z_{t-1} + u_t && \text{(State transition equation)} \end{aligned}$$

- Stata specification:

```
. dsge (y=z) (f.z = {rho}*z, state)
```

- With the `bayes:` prefix:

```
. bayes, prior({rho}, uniform(-1,1)): dsge (y=z) (f.z = {rho}*z, state)
```

An AR(1) model

Output

```
. bayes, prior({rho}, uniform(-1,1)) rseed(20) : ///
>       dsge (y = z) (f.z = {rho}*z, state)
note: initial parameter vector set to means of priors.

Burn-in ...
Simulation ...

Model summary
------------------------------------------------------------------------------
Likelihood:
  y ~ dsgell({rho},{sd(e.z)})

Priors:
      {rho} ~ uniform(-1,1)
  {sd(e.z)} ~ igamma(.01,.01)
------------------------------------------------------------------------------
```

(Output continues on next slide)

An AR(1) model

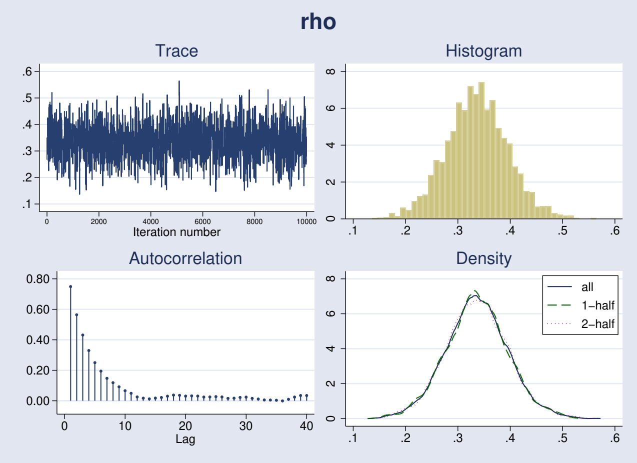
Output II

```
Bayesian linear DSGE model                          MCMC iterations  =     12,500
Random-walk Metropolis-Hastings sampling            Burn-in          =      2,500
                                                    MCMC sample size =     10,000
Sample: 1955q1 thru 2015q4                          Number of obs    =        244
                                                    Acceptance rate  =       .266
                                                    Efficiency:  min =      .1109
                                                                 avg =      .1181
Log marginal-likelihood = -648.62049                             max =      .1253
```

	Mean	Std. dev.	MCSE	Median	Equal-tailed [95% cred.	interval]
rho	.3361959	.0592612	.001674	.3351618	.2176139	.4571248
sd(e.z)	3.340431	.150282	.004513	3.336891	3.060339	3.649831

An AR(1) model
Diagnostics

```
. bayesgraph diagnostics {rho}
```



An AR(1) model

More diagnostics

```
. bayesstats ess

Efficiency summaries    MCMC sample size =     10,000
                        Efficiency:  min =      .1109
                                     avg =      .1181
                                     max =      .1253
```

	ESS	Corr. time	Efficiency
rho	1252.97	7.98	0.1253
sd(e.z)	1108.99	9.02	0.1109

Summary

- Basic syntax of DSGE models:

```
. dsge (model_equations)
```

- Basic syntax of Bayesian DSGE models:

```
. bayes, prior(prior_spec) : dsge (model_equations)
```

- Parameter estimation
- Postestimation diagnostics

Outline

- DSGE models, `dsge`, and `bayes: dsge`
- AR(1) model
- Linear New Keynesian model
- Nonlinear stochastic growth model

Linear DSGE models

- We now return to a small, fully-featured DSGE model
- Equations:

$$
\begin{aligned}
x_t &= E_t x_{t+1} - (r_t - E_t \pi_{t+1} - z_t) && \text{(IS)} \\
\pi_t &= \beta E_t \pi_{t+1} + \kappa x_t && \text{(Phillips Curve)} \\
r_t &= \frac{1}{\beta} \pi_t + w_t && \text{(Taylor Rule)} \\
w_{t+1} &= \rho_w w_t + e_{t+1} \\
z_{t+1} &= \rho_z z_t + \varepsilon_{t+1}
\end{aligned}
$$

- Control equations for output gap, inflation, interest rate
- State equations for monetary and IS disturbances (AR(1))
- Equations are linear in variables, nonlinear in parameters
- Forward-looking elements in the control equations
- Shocks flow into state variables, then into control variables

Linearized New Keynesian model

Data

```
. webuse usmacro2
(Federal Reserve Economic Data - St. Louis Fed, 2017-01-15)

. describe

Contains data from https://www.stata-press.com/data/r17/usmacro2.dta
 Observations:           244                  Federal Reserve Economic Data -
                                                St. Louis Fed, 2017-01-15
    Variables:            11                  1 May 2020 17:52
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-------------------------------------------------------------------------------
Variable      Storage   Display    Value
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daten           int     %td                   Numeric (daily) date
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c               double  %10.0g                Growth rate of consumption
                                                (PCECC96)
n               double  %10.0g                Growth rate of hours worked
                                                (HOANBS)
i               double  %10.0g                Corporate bond interest rate
                                                (AAA)
e               double  %10.0g                Percentage change in US exchange
                                                rate (TWEXBMTH)
-------------------------------------------------------------------------------
```
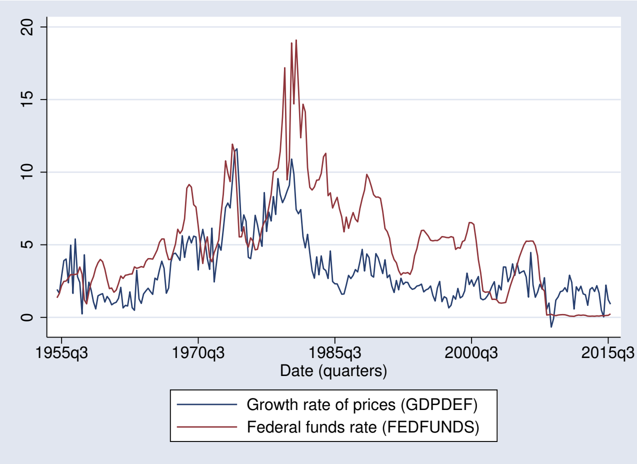

Linearized New Keynesian model

Data

```
. tsline p r, legend(rows(2))
```



Linear New Keynesian model

Model specification

```
. bayes, prior({beta}, beta(10, 10))  prior({kappa}, beta(30, 70))    ///
>        prior({rhow}, beta(10, 10))  prior({rhoz},  beta(35,15))     ///
>        rseed(17) dots:                                              ///
>        dsge (x   = F.x - (r - F.p - z)    , unobserved )    ///
>             (p   = {beta}*F.p + {kappa}*x              )    ///
>             (r   = (1/{beta})*p + w                    )    ///
>             (F.z = {rhoz}*z               , state      )    ///
>             (F.w = {rhow}*w               , state      )
note: initial parameter vector set to means of priors.

Burn-in 2500 aaaaaaaaa1000.........2000..... done
Simulation 10000 .........1000.........2000.........3000.........4000.........5
> 000.........6000.........7000.........8000.........9000.........10000 done
```

Linear New Keynesian model

Estimation header

```
Model summary
------------------------------------------------------------------------------
Likelihood:
  p r ~ dsgell({beta},{kappa},{rhoz},{rhow},{sd(e.z)},{sd(e.w)})

Priors:
             {beta} ~ beta(10,10)
            {kappa} ~ beta(30,70)
             {rhoz} ~ beta(35,15)
             {rhow} ~ beta(10,10)
  {sd(e.z) sd(e.w)} ~ igamma(.01,.01)
------------------------------------------------------------------------------
```

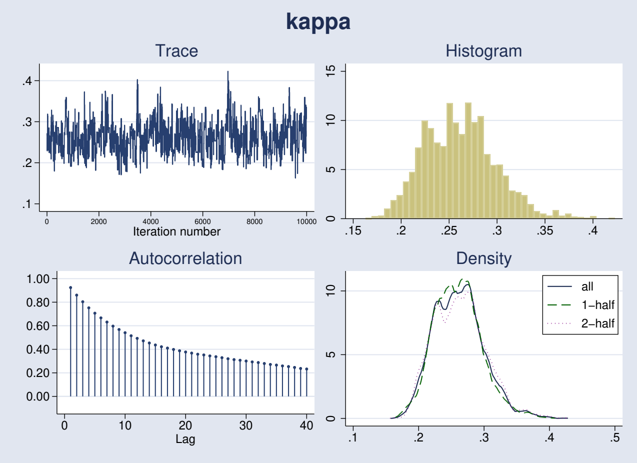
Linear New Keynesian model

Estimation output

```
Bayesian linear DSGE model                         MCMC iterations  =     12,500
Random-walk Metropolis-Hastings sampling           Burn-in          =      2,500
                                                   MCMC sample size =     10,000
Sample: 1955q1 thru 2015q4                         Number of obs    =        244
                                                   Acceptance rate  =      .1523
                                                   Efficiency:  min =     .01375
                                                                avg =     .01964
Log marginal-likelihood = -784.87902                            max =     .02488
```

	Mean	Std. dev.	MCSE	Median	Equal-tailed [95% cred.	interval]
beta	.4731495	.0506063	.003631	.4739432	.3692667	.5735173
kappa	.261336	.0374749	.002812	.2595999	.1971056	.341189
rhoz	.9084647	.0151727	.000962	.9083686	.8783911	.9359358
rhow	.6309735	.033607	.002866	.6322336	.563363	.6972567
sd(e.z)	.7389675	.0738833	.005184	.7357219	.60302	.8981278
sd(e.w)	2.53286	.2537029	.017219	2.495344	2.128193	3.108239

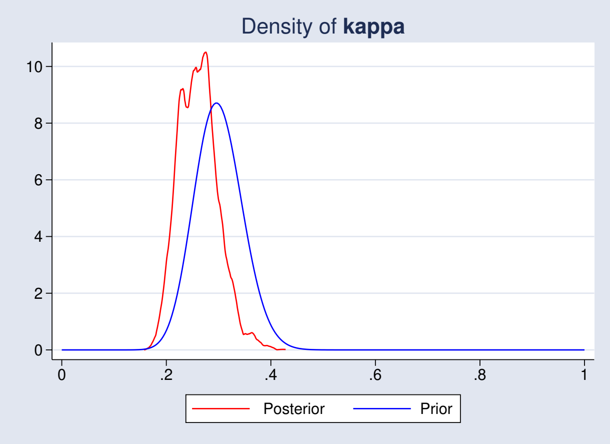
```
. bayesgraph diagnostics kappa
```



Linear New Keynesian model

Prior-posterior plot

```
. bayesgraph kdensity {kappa}, lcolor(red)                  ///
>         addplot(function Prior = betaden(30,70, x),   ///
>         legend(on label(1 "Posterior")) lcolor(blue))
```



Linear New Keynesian model

Diagnostics

```
. bayesstats ess

Efficiency summaries    MCMC sample size =     10,000
                        Efficiency:  min =     .01375
                                     avg =     .01964
                                     max =     .02488
```

	ESS	Corr. time	Efficiency
beta	194.26	51.48	0.0194
kappa	177.56	56.32	0.0178
rhoz	248.80	40.19	0.0249
rhow	137.55	72.70	0.0138
sd(e.z)	203.12	49.23	0.0203
sd(e.w)	217.08	46.07	0.0217

Linear New Keynesian model

Impulse responses

- One key object of interest in DSGE analysis is the impulse response function (IRF)
- IRFs plot the response of model variables to unexpected shocks to a state variable
- A type of counterfactual analysis
- Answers to policy questions: what is the effect of a change in monetary policy (or fiscal policy, oil prices, etc) on variables of interest?

Linear New Keynesian model

Impulse responses

- Stata has the `irf` suite of commands to create, plot, and make tables of IRFs
- Available after `dsge`, `var`, and some other time-series commands
- Now, this suite is extended to work after Bayesian estimation with `bayesirf`
  - `bayesirf set` to set a results file
  - `bayesirf create` to compute IRFs
  - `bayesirf graph` for plots
  - `bayesirf table` for tables
  - and other utility commands

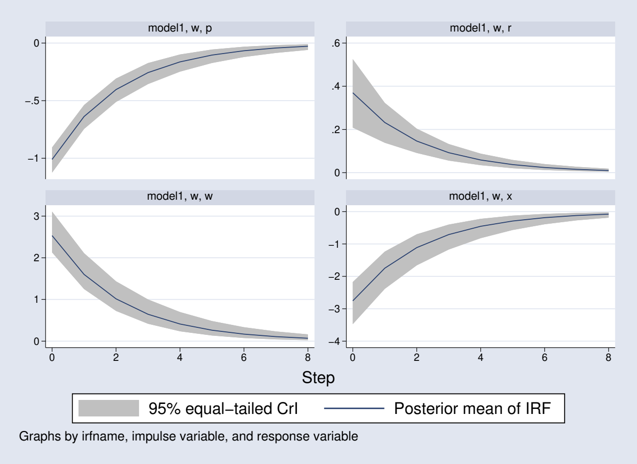
Linear New Keynesian model

Impulse responses

```
. bayesirf set nkirf.irf, replace
(file nkirf.irf created)
(file nkirf.irf now active)

. bayesirf create model1
(file nkirf.irf updated)

. bayesirf graph irf, impulse(w) response(x p r w) byopts(yrescale)
```

Linear New Keynesian model

Impulse responses



Linear New Keynesian model

Underidentified model

- Bayesian estimation can be performed even when the model parameters are not classically identified
- Identification then comes off the prior
- Consider the model:

$$x_t = E_t x_{t+1} - \sigma(r_t - E_t \pi_{t+1} - z_t) \quad \text{(IS)}$$

$$\pi_t = \beta E_t \pi_{t+1} + \kappa x_t \quad \text{(Phillips Curve)}$$

$$r_t = \frac{1}{\psi}\pi_t + w_t \quad \text{(Taylor Rule)}$$

$$w_{t+1} = \rho_w w_t + e_{t+1}$$

$$z_{t+1} = \rho_z z_t + \varepsilon_{t+1}$$

- New parameters (σ, ψ) not identified just from data on inflation and interest rate
- We can bring in prior information to aid estimation

Linear New Keynesian model

Underidentified model: setup

```
. bayes, prior({beta},  beta(95, 5))   prior({kappa}, beta(30,70))     ///
>        prior({sigma}, beta(10,90))   prior({psi},   beta(67,33))     ///
>        prior({rhow},  beta(10, 10))  prior({rhoz},  beta(35,15))     ///
>        rseed(17) dots burnin(5000) mcmcsize(30000):                  ///
>        dsge (x   = F.x - {sigma}*(r - F.p - z)    , unobserved ) ///
>             (p   = {beta}*F.p + {kappa}*x                     ) ///
>             (r   = (1/{psi})*p + w                            ) ///
>             (F.z = {rhoz}*z                 , state           ) ///
>             (F.w = {rhow}*w                 , state           )
note: initial parameter vector set to means of priors.

Burn-in 5000 aaaaaaaaa1000aaaaaaaaa2000aaaa.....3000.........4000.........5000
> done
Simulation 30000 .........1000.........2000.........3000.........4000.........5
> 000.........6000.........7000.........8000.........9000.........10000........
> .11000.........12000.........13000.........14000.........15000.........16000.
> ........17000.........18000.........19000.........20000.........21000........
> .22000.........23000.........24000.........25000.........26000.........27000.
> ........28000.........29000.........30000 done
```

Linear New Keynesian model

Underidentified model: header output

```
Model summary
------------------------------------------------------------------------------
Likelihood:
  p r ~ dsgell({sigma},{beta},{kappa},{psi},{rhoz},{rhow},{sd(e.z)},{sd(e.w)})

Priors:
            {sigma} ~ beta(10,90)
             {beta} ~ beta(95,5)
            {kappa} ~ beta(30,70)
              {psi} ~ beta(67,33)
             {rhoz} ~ beta(35,15)
             {rhow} ~ beta(10,10)
  {sd(e.z) sd(e.w)} ~ igamma(.01,.01)
------------------------------------------------------------------------------
```

Linear New Keynesian model

Underidentified model: estimation output

```
Bayesian linear DSGE model                         MCMC iterations  =     35,000
Random-walk Metropolis-Hastings sampling           Burn-in          =      5,000
                                                   MCMC sample size =     30,000
Sample: 1955q1 thru 2015q4                         Number of obs    =        244
                                                   Acceptance rate  =      .1741
                                                   Efficiency:  min =    .005331
                                                                avg =     .01032
Log marginal-likelihood = -787.73905                            max =     .01974
```

	Mean	Std. dev.	MCSE	Median	Equal-tailed [95% cred.	interval]
sigma	.1443227	.0292876	.001318	.1432416	.088498	.2043906
beta	.9547238	.0203592	.001276	.9576523	.9077723	.9848212
kappa	.3419745	.0457376	.003318	.3415295	.2517864	.4357346
psi	.6527897	.043041	.003403	.6529768	.5686343	.7351054
rhoz	.9078086	.0157278	.00091	.9080455	.8749843	.9369648
rhow	.7546737	.0269813	.001109	.7541327	.7017534	.8085894
sd(e.z)	.6048148	.0950875	.005623	.5951787	.4475909	.8237128
sd(e.w)	1.955303	.1265823	.008904	1.948905	1.734296	2.230285

Linear New Keynesian model

Underidentified model: summaries of functions of parameters

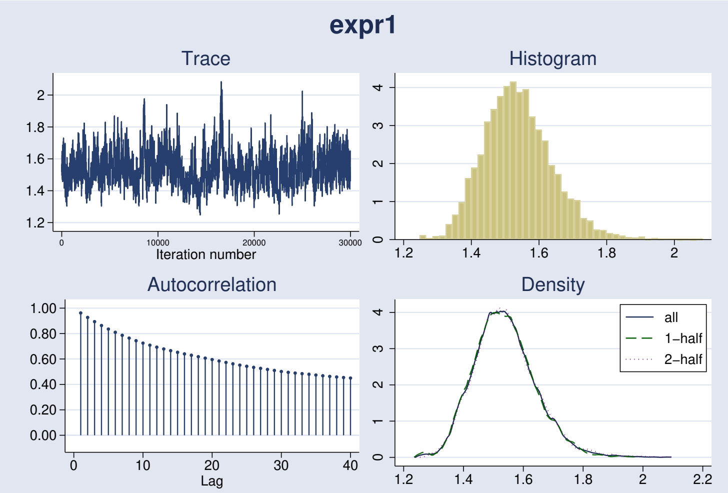
```
. bayesstats summary (1/{psi})
Posterior summary statistics                      MCMC sample size =     30,000
      expr1 : 1/{psi}
```

	Mean	Std. dev.	MCSE	Median	Equal-tailed [95% cred.	interval]
expr1	1.538681	.1035836	.008064	1.531448	1.360349	1.7586

Linear New Keynesian model

Underidentified model: diagnostics of functions of parameters

```
. bayesgraph diagnostics (1/{psi})
```



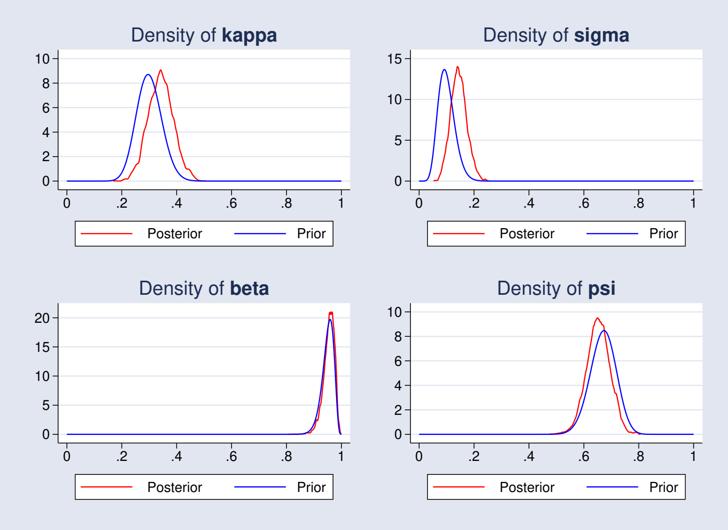
Linear New Keynesian model

Underidentified model: prior/posterior graph setup

```
. bayesgraph kdensity {kappa}, lcolor(red) ///
>         addplot(function Prior=betaden(30,70,x), ///
>         legend(on label(1 "Posterior")) lcolor(blue)) name(kappa) nodraw

.
. bayesgraph kdensity {sigma}, lcolor(red) ///
>         addplot(function Prior=betaden(10,90,x), ///
>         legend(on label(1 "Posterior")) lcolor(blue)) name(sigma) nodraw

.
. bayesgraph kdensity {beta}, lcolor(red) ///
>         addplot(function Prior=betaden(95,5,x), ///
>         legend(on label(1 "Posterior")) lcolor(blue)) name(beta) nodraw

.
. bayesgraph kdensity {psi}, lcolor(red) ///
>         addplot(function Prior=betaden(67,33,x), ///
>         legend(on label(1 "Posterior")) lcolor(blue)) name(psi) nodraw

.
. graph combine kappa sigma beta psi
```

Linear New Keynesian model

Underidentified model: prior/posterior graphs



Outline

- DSGE models, `dsge`, and `bayes: dsge`
- AR(1) model
- Linear New Keynesian model
- Nonlinear stochastic growth model

Nonlinear DSGE models

- Linear DSGE models are linear in variables, potentially nonlinear in parameters
- Nonlinear DSGE models are nonlinear in both variables and parameters
- `dsgenl` estimates the parameters of nonlinear DSGE models by first-order approximation (linearization)
- `bayes: dsgenl` does the same, with Bayesian methods

The stochastic growth model

Equations

$$
\begin{aligned}
\frac{1}{c_t} &= \beta E_t \left[\left(\frac{1}{c_{t+1}} \right) (1 + r_{t+1} - \delta) \right] && \text{(Consumption)} \\
r_t &= \alpha \frac{y_t}{k_t} && \text{(Capital demand)} \\
y_t &= z_t k_t^{\alpha} && \text{(Production function)} \\
k_{t+1} &= y_t - c_t + (1 - \delta) k_t && \text{(Capital accumulation)} \\
\ln z_{t+1} &= \rho \ln z_t + e_{t+1}
\end{aligned}
$$

The stochastic growth model
Setup

```
. bayes, prior({alpha}, beta(30,70))   prior({beta}, beta(95,5))    ///
>        prior({delta}, beta(25,975))  prior({rho}, beta(5, 3))     ///
>        rseed(17) burnin(5000) dots :                              ///
>        dsgenl (1/c       = {beta}*(1/f.c)*(1+f.r-{delta}))            ///
>                (r        = {alpha}*y/k)                               ///
>                (y        = z*k^({alpha}))                             ///
>                (f.k      = y - c + (1-{delta})*k)                     ///
>                (ln(f.z) = {rho}*ln(z))                                ///
>                , exostate(z) endostate(k) observed(y) unobserved(c r)
note: initial parameter vector set to means of priors.

Burn-in 5000 aaaaaaaaa1000aaaaaaaaa2000aaaaaaaaa3000aaaaaa...4000.........5000
> done
Simulation 10000 .........1000.........2000.........3000.........4000.........5
> 000.........6000.........7000.........8000.........9000.........10000 done
```

The stochastic growth model

Header output

```
Model summary
------------------------------------------------------------------------------
Likelihood:
  y ~ dsgell({beta},{delta},{alpha},{rho},{sd(e.z)})

Priors:
     {beta} ~ beta(95,5)
    {delta} ~ beta(25,975)
    {alpha} ~ beta(30,70)
      {rho} ~ beta(5,3)
  {sd(e.z)} ~ igamma(.01,.01)
------------------------------------------------------------------------------
```

The stochastic growth model

Estimation output

```
Bayesian first-order DSGE model                    MCMC iterations  =     15,000
Random-walk Metropolis-Hastings sampling           Burn-in          =      5,000
                                                   MCMC sample size =     10,000
Sample: 1955q1 thru 2015q4                         Number of obs    =        244
                                                   Acceptance rate  =      .2506
                                                   Efficiency:  min =     .04563
                                                                avg =     .04999
Log marginal-likelihood = -649.82949                            max =     .05552
```

	Mean	Std. dev.	MCSE	Median	Equal-tailed [95% cred.	interval]
beta	.9554009	.0194803	.00086	.9582636	.9104263	.9847218
delta	.0250477	.0048846	.000207	.0247132	.0163193	.0357851
alpha	.2962864	.0442748	.002073	.2958201	.2122214	.3837115
rho	.3064437	.0584439	.002654	.3047101	.1939408	.422685
sd(e.z)	3.359195	.152429	.006891	3.360512	3.068458	3.658345

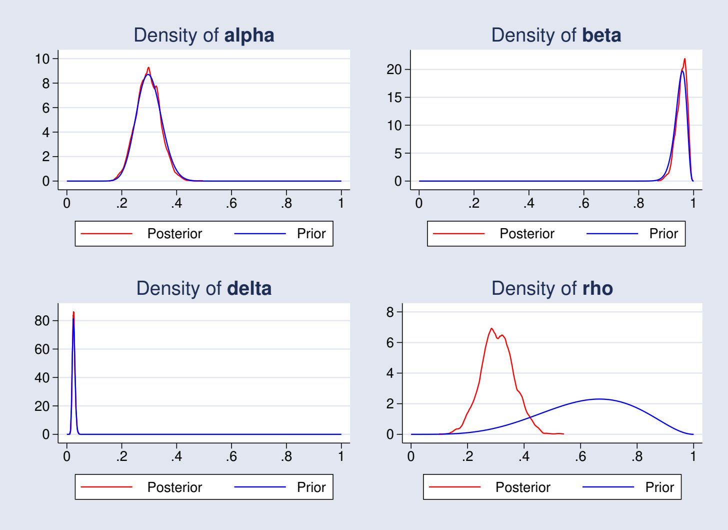
The stochastic growth model

Prior/posterior graphs

```
. bayesgraph kdensity {alpha}, lcolor(red) ///
>         addplot(function Prior=betaden(30,70,x), ///
>         legend(on label(1 "Posterior")) lcolor(blue)) name(alpha) nodraw

.
. bayesgraph kdensity {beta}, lcolor(red) ///
>         addplot(function Prior=betaden(95, 5,x), ///
>         legend(on label(1 "Posterior")) lcolor(blue)) name(beta) nodraw

.
. bayesgraph kdensity {delta}, lcolor(red) ///
>         addplot(function Prior=betaden(25,975,x), ///
>         legend(on label(1 "Posterior")) lcolor(blue)) name(delta) nodraw

.
. bayesgraph kdensity {rho}, lcolor(red) ///
>         addplot(function Prior=betaden(5,3,x), ///
>         legend(on label(1 "Posterior")) lcolor(blue)) name(rho) nodraw

.
. graph combine alpha beta delta rho
```

The stochastic growth model

Prior/posterior graphs



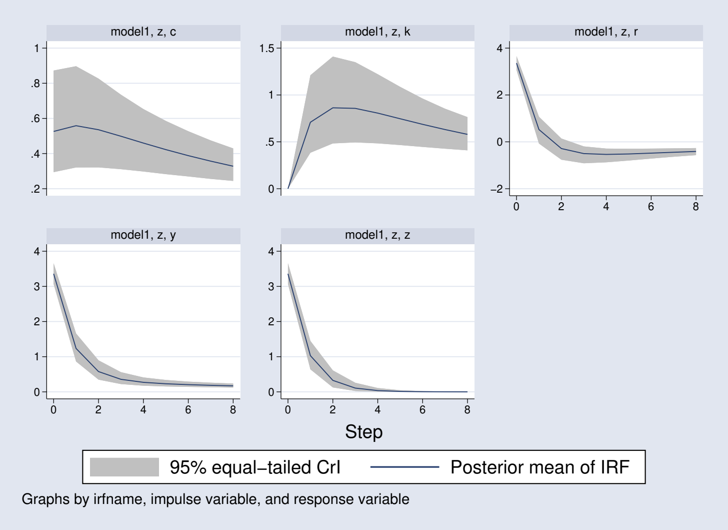
The stochastic growth model

Impulse responses

```
. bayesirf set stochmodel, replace
(file stochmodel.irf created)
(file stochmodel.irf now active)
. bayesirf create model1
(file stochmodel.irf updated)
. bayesirf graph irf, impulse(z) byopts(yrescale)
```

The stochastic growth model

Impulse responses



Final thoughts

- the `bayes:` prefix now supports `dsge` and `dsgenl`
- Bayesian impulse response functions supported with `bayesirf`

Thank you!