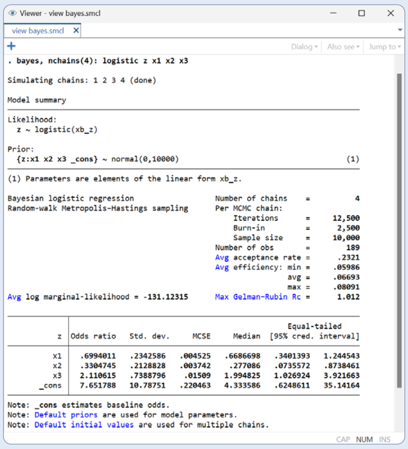
Stata Features

Bayesian analysis

Your Bayesian analysis in Stata can be as simple or as complex as your research problem.

- Thousands of built-in models
- Add your own models
- Prefix your command with **bayes:**
- Adaptive Metropolis–Hastings
- Gibbs sampling
- Multiple chains
- Convergence diagnostics
- Explore distributions
- Model goodness of fit
- Posterior predictive *p*-values
- Posterior summaries
- Hypothesis testing
- Model comparison
- Predictions
- Model averaging
- Variable selection New
- More



Fit regression models

Linear regression

```
. bayes: regress y x1 x2 x3
```

Logistic regression

```
. bayes: logistic z x1 x2 x3
```

Quantile regression

```
. bayes: qreg y x1 x2, quantile(0.75)
```

Multilevel regression

```
. bayes: mixed y x1 x2 x3 || id:
```

Vector autoregression

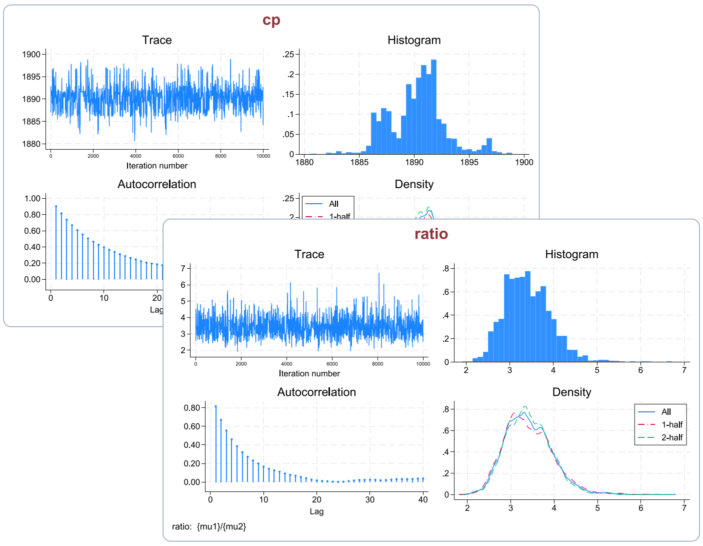
```
. bayes: var y1 y2 y3, lags(1/3) exog(x1 x2)
```

Specify multiple chains

```
. bayes, nchains(4): logistic z x1 x2 x3
```

Check convergence

```
. bayesgraph diagnostics {cp}
                   (ratio: {mu1}/{mu2})
```



Fit general models

Multilevel meta-analysis model

```
. bayesmh lnOR U[trial], noconstant likelihood(normal(var))
                         prior({U[trial]}, normal({theta},{tau2}))
                         prior({theta}, normal(0,10000))
                         prior({tau2}, igamma(0.0001,0.0001))
                         block({theta tau2}, gibbs split)
```

Nonlinear Poisson model: Change-point analysis

```
. bayesmh count, likelihood(dpoisson({mu1}*sign(year<{cp})+{mu2}*sign(year>={cp})))
                 prior({mu1 mu2}, flat)
                 prior({cp}, uniform(1851,1962))
                 initial({mu1 mu2} 1 {cp} 1906)
```

Program your own models

Hurdle model

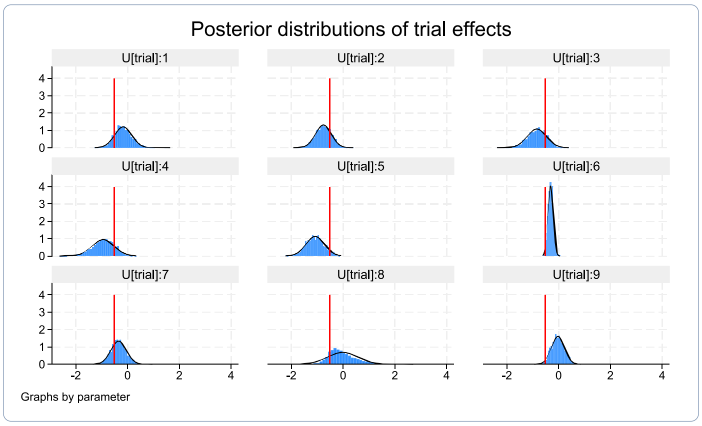
```
. bayesmh (hours age) (hours0 commute), llevaluator(mychurdle, parameters({lnsig}))
                                        prior({hours:} {hours0:} {lnsig}, flat)
```

```
program mychurdle
        version 19.5
        args lnfj xb xg lnsig
        tempvar sig
        scalar `sig' = exp(`lnsig')
        qui replace `lnfj' =
        normal(`xg') if $MH_touse
        qui replace `lnfj' = log(1 - `lnfj') if $MH_y1 <= 0 & $MH_touse
        qui replace `lnfj' = log(`lnfj') - log(normal(`xb'/`sig')) + ///
        log(normalden($MH_y1, `xb', `sig')) if $MH_y1 > 0 & $MH_touse
end
```

Perform inference

Explore distributions

```
. bayesgraph histogram {U[trial]}, ...
```



Test a hypothesis

```
. bayestest interval {mu1}/{mu2}, lower(3)
```

```
Interval tests                MCMC sample size = 10,000

      prob1 : {mu1}/{mu2} > 3
```

	Mean	Std. dev.	MCSE
prob1	.7147	0.45158	.0216545

Compare models

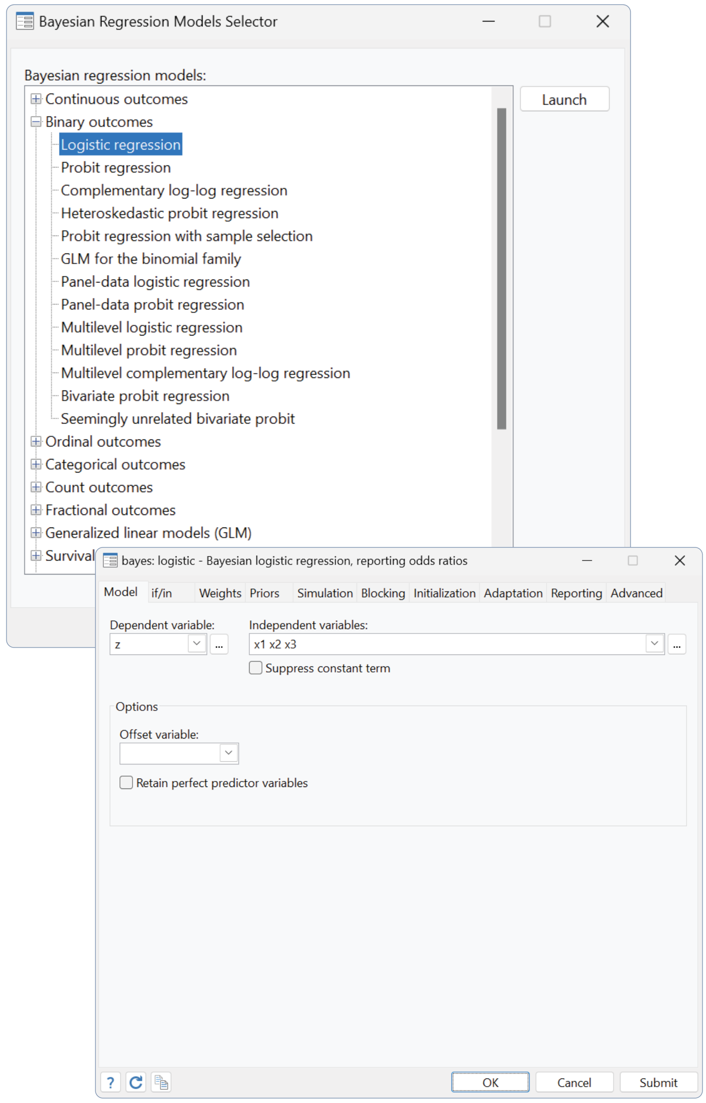
```
. bayesstats ic model1 model2
```

Bayesian information criteria

	DIC	log(ML)	log(BF)
model1	472.0359	-242.5827	.
model2	470.8157	-235.7438	6.838942

Note: Marginal likelihood (ML) is computed
using Laplace-Metropolis approximation.

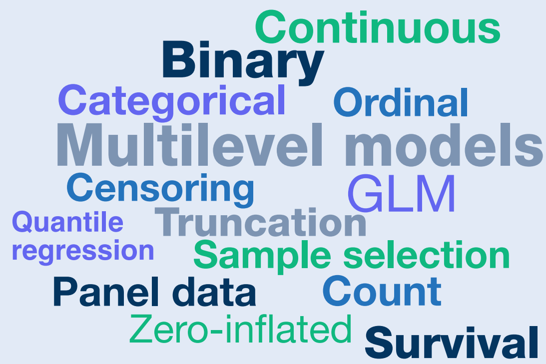
Perform any analyses using GUI



Regression models

Simply prefix your regression command with **bayes:**

- Over 60 likelihood models supported, including multilevel, survival, GLM, VAR, DSGE, and more
- Censoring, truncation, sample selection
- Intuitive and elegant model specification
- Default and custom priors
- Comprehensive Bayesian-features support



Linear regression

Use default normal priors for coefficients and inverse-gamma prior for variance

```
. bayes: regress y x1 x2
```

```
Viewer - view bayes_regress.smcl
view bayes_regress.smcl
Dialog  Also see  Jump to

. bayes: regress y x1 x2

Burn-in ...
Simulation ...

Model summary
------------------------------------------------------------------------------
Likelihood:
  y ~ regress(xb_y,{sigma2})

Priors:
  {y:x1 x2 _cons} ~ normal(0,10000)                                        (1)
         {sigma2} ~ igamma(.01,.01)
------------------------------------------------------------------------------
(1) Parameters are elements of the linear form xb_y.

Bayesian linear regression                       MCMC iterations  =     12,500
Random-walk Metropolis-Hastings sampling         Burn-in          =      2,500
                                                 MCMC sample size =     10,000
                                                 Number of obs    =         74
                                                 Acceptance rate  =      .3855
                                                 Efficiency:  min =     .07633
                                                              avg =      .1159
Log marginal-likelihood = -218.13296                          max =      .1694

------------------------------------------------------------------------------
             |                                                Equal-tailed
             |      Mean   Std. dev.     MCSE     Median  [95% cred. interval]
-------------+----------------------------------------------------------------
y            |
          x1 | -.3951938   .1637576   .004942  -.3960287  -.7201108  -.0847018
          x2 | -.7656255   .5779397   .017594  -.7682354  -1.867728   .3611014
       _cons |  47.60132    6.36683   .230446    47.5305   35.33225     60.082
-------------+----------------------------------------------------------------
      sigma2 |  11.97461   2.055562    .04994   11.77334   8.507135     16.573
------------------------------------------------------------------------------
Note: Default priors are used for model parameters.
CAP  NUM  INS
```

Use Gibbs sampling

```
. bayes, gibbs: regress y x1 x2
```

Logistic regression

Use default normal priors for coefficients

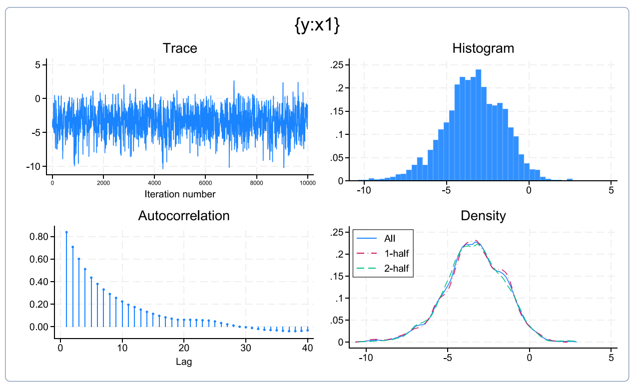
```
. bayes: logistic y x1 x2
```

Use custom Cauchy priors for coefficients on **x1** and **x2**

```
. bayes, prior({y:x1 x2}, cauchy(0,2.5)):
         logistic y x1 x2
```

Check convergence of coefficient on **x1**

```
. bayesgraph diagnostics {y:x1}
```



Quantile regression

Fit a Bayesian quantile regression of the 75th percentile of **y** conditional on **x1** and **x2**

```
. bayes: qreg y x1 x2, quantile(0.75)
```

```
Viewer - view bayes_qr.smcl
view bayes_qr.smcl
Dialog  Also see  Jump to

------------------------------------------------------------------------------
             |                                                Equal-tailed
             |      Mean   Std. dev.     MCSE     Median  [95% cred. interval]
-------------+----------------------------------------------------------------
y_q75        |
          x1 | -.6340726   .2430469   .007104  -.6476498   -1.09264  -.1094803
          x2 | -.1233109   .2586184   .008309  -.1191342  -.6803071   .3658962
       _cons |  .5602515   .0397071   .001344   .5577472   .4903082   .6465843
-------------+----------------------------------------------------------------
       sigma |  .1180982   .0139742   .000303   .1172271   .0939265   .1483774
------------------------------------------------------------------------------
CAP  NUM  INS
```

Generalized linear model

Use burn-in of 1,000 and MCMC size of 5,000

```
. bayes, burnin(1000) mcmcsize(5000):
        glm y x1 x2, family(binomial) link(log)
```

Test that coefficient **{y:x1}** is greater than 4

```
. bayestest interval {y:x1}, lower(4)
```

Viewer - view bayes_interval.smcl

```
. bayestest interval {y:x1}, lower(4)

Interval tests     MCMC sample size =    10,000

       prob1 : {y:x1} > 4

-----------------------------------------------
             |      Mean    Std. dev.      MCSE
-------------+---------------------------------
       prob1 |     .7881     0.40867   .0125451
-----------------------------------------------
```

Survival regression

Declare survival data

```
. stset time, failure(died)
```

Fit Bayesian exponential regression

```
. bayes, saving(mcmc_exp): streg x1 x2,
        distribution(exponential)

. estimates store exp
```

Fit Bayesian Weibull regression

```
. bayes, saving(mcmc_weibull): streg x1 x2,
        distribution(weibull)

. estimates store weibull
```

Compare models using the Bayes factor

```
. bayesstats ic exp weibull, bayesfactor
```

Viewer - view bayes_ic.smcl

```
. bayesstats ic exp weibull, bayesfactor

Bayesian information criteria

----------------------------------------------
             |       DIC    log(ML)        BF
-------------+--------------------------------
         exp |  103.4405  -71.04365         .
     weibull |  92.02015  -74.79336  .0235246
----------------------------------------------
Note: Marginal likelihood (ML) is computed
      using Laplace-Metropolis approximation.
```

Compare models using posterior probabilities

```
. bayestest model exp weibull
```

Viewer - view bayes_model.smcl

```
. bayestest model exp weibull

Bayesian model tests

---------------------------------------------
             |   log(ML)      P(M)    P(M|y)
-------------+-------------------------------
         exp |  -71.0436    0.5000    0.9770
     weibull |  -74.7934    0.5000    0.0230
---------------------------------------------
Note: Marginal likelihood (ML) is computed using
      Laplace-Metropolis approximation.
```

Other regression models

Ordered logistic regression

```
. bayes: ologit y x1 x2
```

Conditional logistic regression

```
. bayes: clogit y x1 x2, group(id)
```

Poisson regression

```
. bayes: poisson y x1 x2
```

Truncated Poisson regression

```
. bayes: tpoisson y x1 x2, ll(10)
```

Zero-inflated negative binomial regression

```
. bayes: zinb y x1 x2, inflated(z1 z2)
```

Tobit regression

```
. bayes: tobit y x1 x2, ul(20)
```

Heteroskedastic probit regression

```
. bayes: hetprobit y x1 x2, het(xhet)
```

Heckman selection model

```
. bayes: heckman y x1 x2, select(x1 x2 x3)
```

Multivariate regression

```
. bayes: mvreg y1 y2 y3 = x1 x2
```

Multilevel regression

```
. bayes: mixed y x1 x2 || id:
```

Vector autoregressive (VAR)

```
. bayes: var y1 y2 y3, lags(1/3) exog(x1 x2)
```

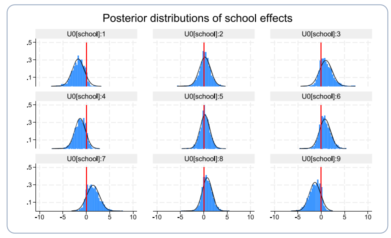
And more

```
. bayes: ...
```

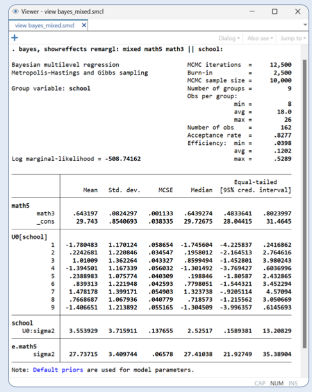
Learn more about regression models at
stata.com/bayesian-regression-models

Multilevel models

Small number of groups?
Many hierarchical levels?
Want posterior distributions of random effects?



- Continuous, censored, binary, ordinal, and count outcomes
- Support for GLM and survival methods
- Random intercepts and coefficients
- Nested and crossed effects
- Multiple levels of hierarchy
- Random-effects covariance structures
- Multivariate nonlinear multilevel models
- Comprehensive Bayesian-features support



Viewer - view bayes_mixed.smcl

```
. bayes, showreffects remargl: mixed math5 math3 || school:

Bayesian multilevel regression                   MCMC iterations  =     12,500
Metropolis-Hastings and Gibbs sampling           Burn-in          =      2,500
                                                 MCMC sample size =     10,000
Group variable: school                           Number of groups =          9
                                                 Obs per group:
                                                              min =          8
                                                              avg =       18.0
                                                              max =         26
                                                 Number of obs    =        162
                                                 Acceptance rate  =      .8277
                                                 Efficiency:  min =      .0398
                                                              avg =      .1202
Log marginal-likelihood = -508.74162                          max =      .5289

                                                            Equal-tailed
             |      Mean   Std. dev.     MCSE     Median  [95% cred. interval]
-------------+-----------------------------------------------------------------
math5        |
       math3 |   .643197   .0824297   .001133   .6439274   .4833641   .8023997
       _cons |    29.743   .8540693   .038335   29.72675   28.04415    31.4645
-------------+-----------------------------------------------------------------
U0[school]   |
           1 | -1.780483   1.170124   .058654  -1.745604  -4.225837   .2416862
           2 |  .2242681   1.220846   .034547   .1958012  -2.164513   2.764616
           3 |   1.01009   1.362264   .043327   .8599494  -1.452801   3.980243
           4 | -1.394501   1.167339   .056032  -1.301492  -3.769427   .6036996
           5 |  .2388983   1.075774   .040309    .198846   -1.80587   2.432865
           6 |   .839313   1.221948   .042593   .7798051  -1.544321   3.452294
           7 |  1.478178   1.399171   .054903   1.323738  -.9205114    4.57094
           8 |  .7668687   1.067936   .040779    .718573  -1.215562   3.050669
           9 | -1.406651   1.213892   .055165  -1.304509  -3.996357   .6145693
-------------+-----------------------------------------------------------------
school       |
   U0:sigma2 |  3.553929   3.715911   .137655    2.52517   .1589381   13.20829
-------------+-----------------------------------------------------------------
e.math5      |
      sigma2 |  27.73715   3.409744    .06578   27.41038   21.92749   35.38904
-------------------------------------------------------------------------------
Note: Default priors are used for model parameters.
```

Two-level models: Random intercepts

Fit regression of **math5** on **math3** with random intercepts by **school**

```
. bayes: mixed math5 math3 || school:
```

Display estimates of random effects

```
. bayes, showreffects:
         mixed math5 math3 || school:
```

(See output above)

Specify custom uniform priors instead of default normal priors for coefficients

```
. bayes, prior({math5:math3 _cons},
         uniform(-50,50)):
         mixed math5 math3 || school:
```

Plot posterior distributions of random intercepts

```
. bayesgraph histogram {U0}, byparm
```

(See graph above)

Two-level models: Random coefficients

Add random coefficient on **math3** by **school**

```
. bayes: mixed math5 math3 || school: math3
```

Specify unstructured covariance for random effects

```
. bayes: mixed math5 math3 || school: math3,
         covariance(unstructured)
```

Three-level models

Add random intercepts for teachers nested within schools

```
. bayes: mixed math5 math3 || school: || teacher:
```

Crossed-effects models

Include crossed random effects of primary and secondary schools

```
. bayes: mixed math5 math3 ||
         _all: R.primary || secondary:
```

Other multilevel models

Logistic regression

```
. bayes: melogit y x1 x2 || id:
```

Poisson regression

```
. bayes: mepoisson y x1 x2 || id:
```

Generalized linear model

```
. bayes: meglm y x1 x2 || id:,
         family(binomial) link(cloglog)
```

Ordered logistic regression

```
. bayes: meologit y x1 x2 || id:
```

Survival regression

```
. bayes: mestreg x1 x2 || id:,
         distribution(weibull)
```

And more

```
. bayes: any multilevel command ...
```

Learn more about multilevel models at
stata.com/bayesian-multilevel-models

Multiple chains, predictions, and more

- Multiple chains
- Gelman–Rubin convergence diagnostics
- Bayesian predictions
- Posterior summaries of simulated values
- MCMC replicates
- Posterior predictive *p*-values

Two-level models: Random coefficients

Use option **nchains()** with **bayes:** or **bayesmh** to simulate multiple chains

Fit regression of **y** on covariates **x1** through **x10**, and generate three chains

Viewer - view bayes_chains.smcl

view bayes_chains.smcl

Dialog Also see Jump to

```
. bayes, nchains(3): regress y x1-x10

Chain 1
  Burn-in ...
  Simulation ...

Chain 2
  Burn-in ...
  Simulation ...

Chain 3
  Burn-in ...
  Simulation ...

Model summary
------------------------------------------------------------------------------
Likelihood:
  y ~ regress(xb_y,{sigma2})

Priors:
  {y:x1 x2 x3 x4 x5 x6 x7 x8 x9 x10 _cons} ~ normal(0,10000)             (1)
                                {sigma2} ~ igamma(.01,.01)
------------------------------------------------------------------------------
(1) Parameters are elements of the linear form xb_y.

Bayesian linear regression                       Number of chains    =        3
Random-walk Metropolis-Hastings sampling         Per MCMC chain:
                                                     Iterations      =   12,500
                                                     Burn-in         =    2,500
                                                     Sample size     =   10,000
                                                 Number of obs       =      442
                                                 Avg acceptance rate =     .321
                                                 Avg efficiency: min =  .003771
                                                                 avg =   .01886
                                                                 max =    .1142
Avg log marginal-likelihood = -2457.6885         Max Gelman-Rubin Rc =    4.543

------------------------------------------------------------------------------
             |                                                Equal-tailed
             |      Mean   Std. dev.     MCSE     Median  [95% cred. interval]
-------------+----------------------------------------------------------------
y            |
          x1 |  81.50951   87.57016   4.06945    71.7336  -50.84804   234.4335
          x2 | -167.0296    71.9136   6.76093   -167.887   -289.098  -42.73281
          x3 |  352.3836   99.94654   6.13795    360.123    193.378   505.5432
          x4 |  286.0075   78.16619   5.23075   275.4511   174.2242   426.8137
          x5 | -273.1433   164.7453    14.618  -295.8386  -501.8144  -16.60783
          x6 |   165.232    178.513   8.84052    231.598  -125.8265   352.7025
          x7 | -94.36373   114.5865   7.16308  -106.0647  -263.5826   99.65676
          x8 |   109.925   162.0595   13.0143   134.8212  -155.8764   332.5971
          x9 |   483.243   102.1253   6.00414   495.4546   307.5461   627.0424
         x10 |  42.76467    117.208   6.29098   65.24344  -146.8923    198.615
       _cons |  152.4957   2.780968   .103842   152.4606   147.3315   157.9954
-------------+----------------------------------------------------------------
      sigma2 |   3110.56   221.9696   3.79219   3100.067   2707.435   3566.951
------------------------------------------------------------------------------
Note: Default priors are used for model parameters.
Note: Default initial values are used for multiple chains.
Note: There is a high autocorrelation after 500 lags in at least one of the
      chains.
```

CAP NUM INS

Gelman–Rubin convergence diagnostics

Check Gelman–Rubin convergence diagnostics

Viewer - view bayes_grubin.smcl

view bayes_grubin.smcl

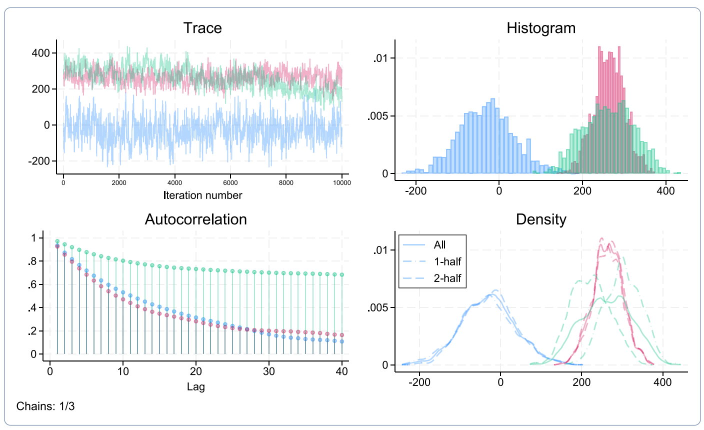
Dialog Also see Jump to

```
. bayesstats grubin, sort

Gelman-Rubin convergence diagnostic

Number of chains     =          3
MCMC size, per chain =     10,000
Max Gelman-Rubin Rc  =   4.542823

-----------------------------
             |         Rc
-------------+---------------
y            |
          x6 |   4.542823
          x8 |   3.376646
          x5 |   3.184339
         x10 |   3.089546
          x3 |   2.543104
          x7 |   2.447089
          x4 |   2.421061
          x1 |    2.40928
          x9 |   2.389624
          x2 |   1.680013
       _cons |   1.082658
-------------+---------------
      sigma2 |   1.023543
-----------------------------
Convergence rule: Rc < 1.1
```

CAP NUM INS

Explore convergence visually for coefficient of **x6**

```
. bayesgraph diagnostics {y:x6}
```



Bayesian predictions

- Predict new values
- Check model fit using posterior predictive checks
- Compute functions of predicted values
- Specify your own prediction functions
- Obtain posterior summaries of predicted values
- Generate MCMC replicates
- Compute posterior predictive *p*-values

Bayesian predictions are outcome values simulated from the posterior predictive distribution. They are useful for predicting new outcome values and for checking model fit. Let's use **bayesmh** to fit a general Bayesian model.

```
. bayesmh y ..., likelihood(...) prior(...)
```

Posterior summaries of predictions

Compute posterior mean and credible intervals for all observations, and store them in variables **pmean**, **cril**, and **criu**

```
. bayespredict pmean, mean
. bayespredict cril criu, cri
```

Viewer - view bayes_predict.smcl

```
. list y pmean cril criu in 1/10

     +-----------------------------------+
     |     y   pmean    cril    criu     |
     |-----------------------------------|
  1. | 2.933   3.111   2.014   4.230     |
  2. | 4.614   4.478   3.362   5.576     |
  3. | 1.654   2.034   0.936   3.115     |
  4. | 2.025   2.234   1.130   3.362     |
  5. | 3.165   2.894   1.790   4.014     |
     |-----------------------------------|
  6. | 1.372   2.337   1.227   3.452     |
  7. | 2.921   3.253   2.127   4.372     |
  8. | 2.699   2.274   1.158   3.359     |
  9. | 1.198   1.228   0.124   2.312     |
 10. | 3.097   2.767   1.655   3.872     |
     +-----------------------------------+
```

Posterior predictive *p*-values

Simulate predictions for outcome **y**, and save them in **y_pred.dta**

```
. bayespredict {_ysim}, saving(y_pred)
```

Compute posterior predictive *p*-values; use Mata's built-in functions and your own

Viewer - view bayes_ppvalues.smcl

```
. bayesstats ppvalues (mean:@mean({_ysim})) (min:@min({_ysim})) (max:@max({_ysim}))
> (skew:@myskew({_ysim})) using y_pred

Posterior predictive summary   MCMC sample size =    10,000

-----------------------------------------------------
           T |     Mean   Std. dev.  E(T_obs)  P(T>=T_obs)
-------------+---------------------------------------
        mean | 3.045143   .0787588   3.044554      .5026
         min | .5130189   .3401942   1.049675      .0365
         max |  5.84806   .3703789   5.703145       .626
        skew | .1471358   .1660461   .1555046      .4806
-----------------------------------------------------
Note: P(T>=T_obs) close to 0 or 1 indicates lack of fit.
```

Viewer - view bayes_skew.smcl

```
. mata:
------------------------------------- mata (type end to exit) ---------
: real scalar myskew(real colvector x) {
>         return (sqrt(length(x))*sum((x:-mean(x)):^3)/(sum((x:-mean(x)):^2)^1.5))
> }

: end
-----------------------------------------------------------------------
```

MCMC replicates

Compute 6 MCMC replicates, and store them in variables **yrep1**, **yrep2**, and so on

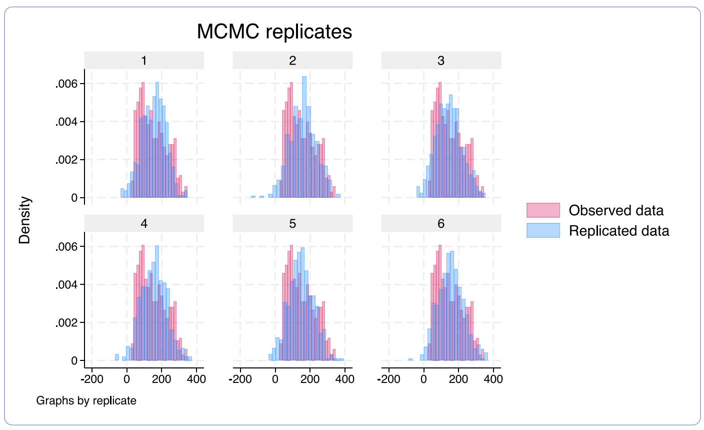
```
. bayesreps yrep*, nreps(6)
```

List the first 10 observations

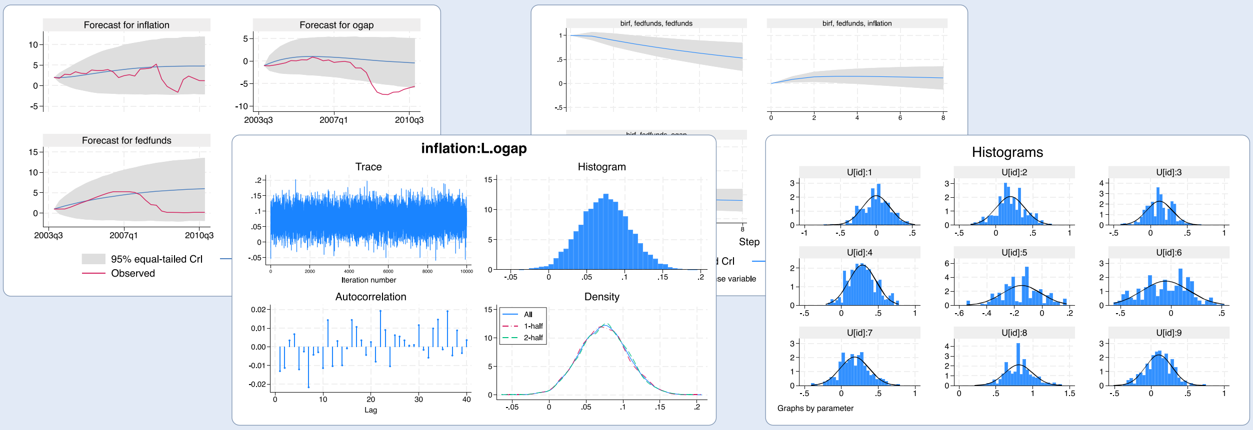
Viewer - view bayes_reps.smcl

```
. list y yrep* in 1/10

     +---------------------------------------------------+
     |     y   yrep1   yrep2   yrep3   yrep4   yrep5   yrep6 |
     |---------------------------------------------------|
  1. | 2.933   3.496   1.416   3.852   2.667   3.621   3.229 |
  2. | 4.614   4.794   3.462   4.354   6.245   3.848   4.822 |
  3. | 1.654   2.068   2.136   1.949   1.395   2.894   2.613 |
  4. | 2.025   2.568   2.234   2.780   1.966   1.804   2.230 |
  5. | 3.165   2.980   2.180   3.610   2.075   2.526   1.754 |
     |---------------------------------------------------|
  6. | 1.372   1.584   2.110   2.932   0.956   2.149   2.438 |
  7. | 2.921   4.087   3.161   3.570   2.687   4.051   3.766 |
  8. | 2.699   1.731   1.846   2.216   2.065   2.109   1.994 |
  9. | 1.198   1.615   1.039   1.530   0.612   1.092   1.478 |
 10. | 3.097   2.281   2.774   2.799   2.162   4.188   3.107 |
     +---------------------------------------------------+
```

Plot distributions of MCMC replicates



Bayesian econometrics

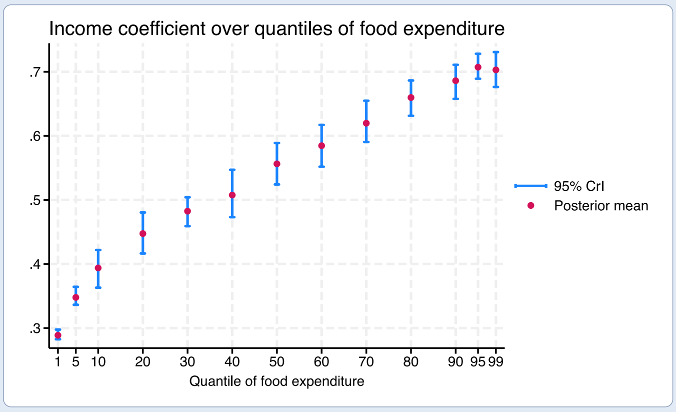


- Panel-data models
- Dynamic forecasting
- VAR models
- IRF and FEVD analysis
- Linear and nonlinear DSGE models
- And more

stata.com/bayesian-econometrics

New in Stata 19

- Bayesian variable selection
  - Variable selection for linear models
  - Account for model uncertainty
  - Inclusion probabilities
- Bayesian quantile regression
- Bayesian asymmetric Laplace model
- Bayesian bootstrap estimation
- Support for half-Cauchy and Rayleigh priors
- Gibbs sampling for normal linear models with Laplace priors
- User-defined evaluators with **bayesmh** now support
  - Efficient estimation of random effects
  - Predictions in evaluators



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