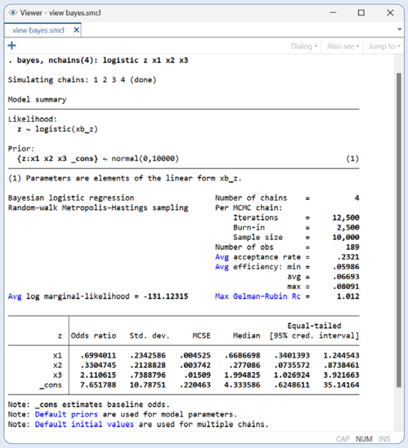
STATA

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



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

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

Simulating chains: 1 2 3 4 (done)

Model summary
------------------------------------------------------------------------------
Likelihood:
  z ~ logistic(xb_z)

Prior:
  {z:x1 x2 x3 _cons} ~ normal(0,10000)                                     (1)
------------------------------------------------------------------------------
(1) Parameters are elements of the linear form xb_z.

Bayesian logistic regression                   Number of chains    =         4
Random-walk Metropolis-Hastings sampling       Per MCMC chain:
                                                   Iterations      =    12,500
                                                   Burn-in         =     2,500
                                                   Sample size     =    10,000
                                               Number of obs       =       189
                                               Avg acceptance rate =     .2321
                                               Avg efficiency: min =    .05986
                                                               avg =    .06693
                                                               max =    .08091
Avg log marginal-likelihood = -131.12315       Max Gelman-Rubin Rc =     1.012

------------------------------------------------------------------------------
             |                                                Equal-tailed
           z | Odds ratio   Std. dev.     MCSE     Median  [95% cred. interval]
-------------+----------------------------------------------------------------
          x1 |   .6994011   .2342586   .004525   .6686698   .3401393   1.244543
          x2 |   .3304745   .2128828   .003742    .277086   .0735572   .8738461
          x3 |   2.110615   .7388796    .01509   1.994825   1.026924   3.921663
       _cons |   7.651788   10.78751   .220463   4.333586   .6248611   35.14164
------------------------------------------------------------------------------
Note: _cons estimates baseline odds.
Note: Default priors are used for model parameters.
Note: Default initial values are used for multiple chains.

CAP NUM INS
```

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

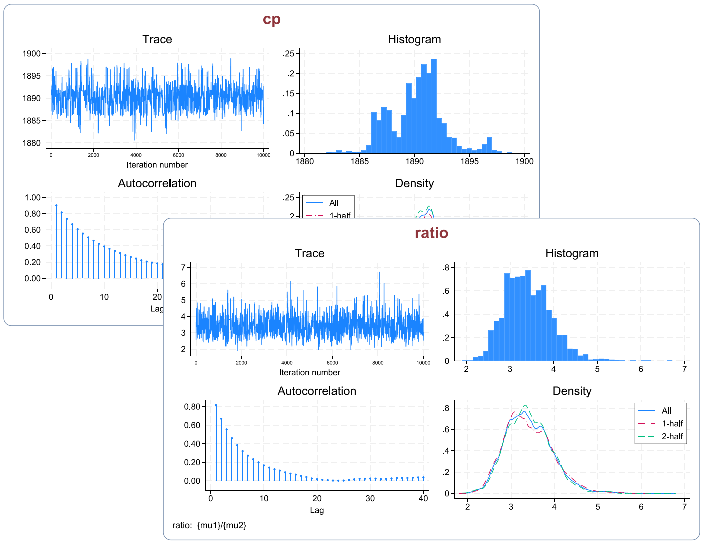
```
. bayes: var y1 y2 y3, lags(1/3) exog(x1 x2)
```

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

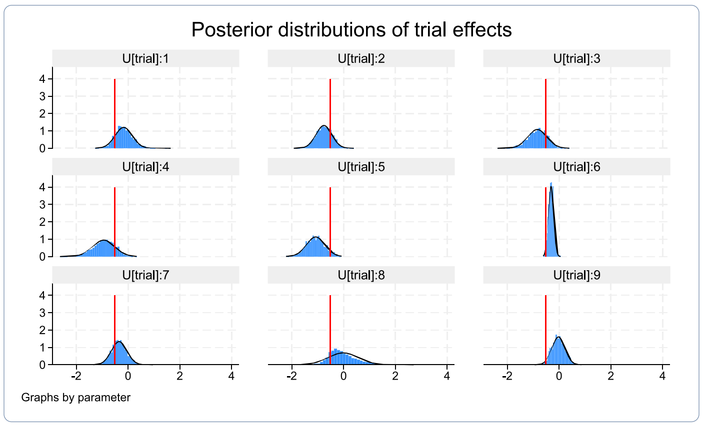
```
. bayesmh (hours age) (hours0 commute), llevaluator(mychurdle, parameters({lnsig}))
                                          prior({hours:} {hours0:} {lnsig}, flat)
```

```
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

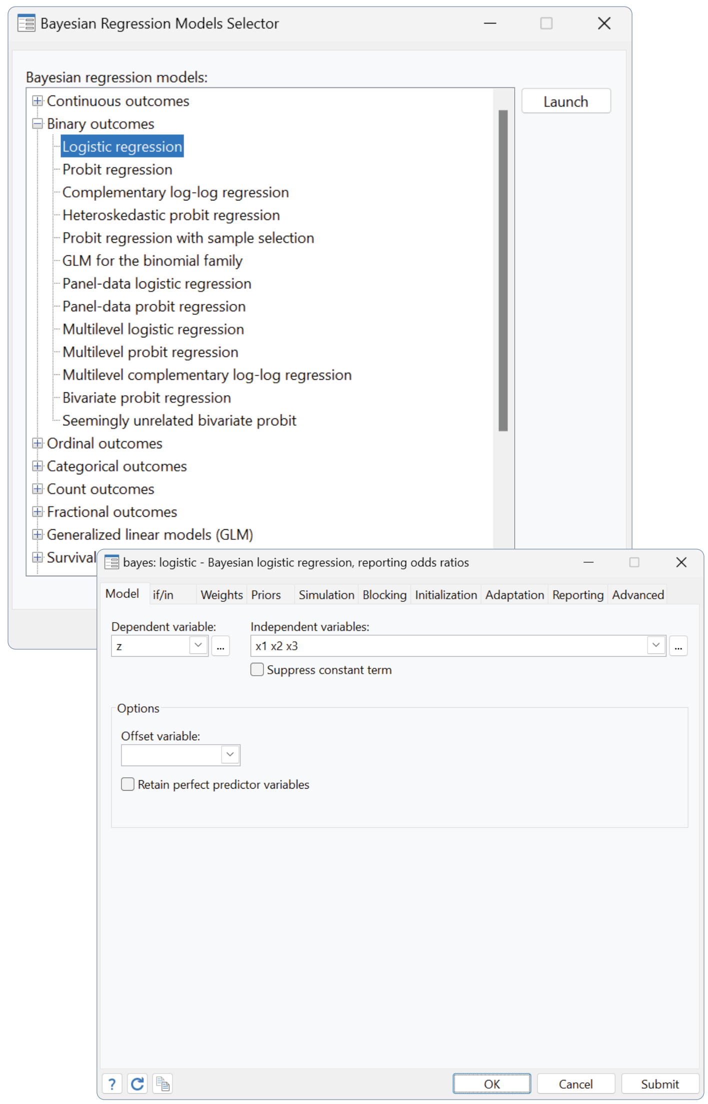
```
. bayesstats ic model1 model2
```

```
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.
```

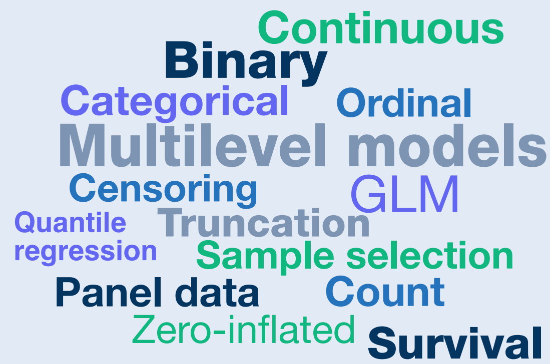
Perform any analyses using GUI



Regression models

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

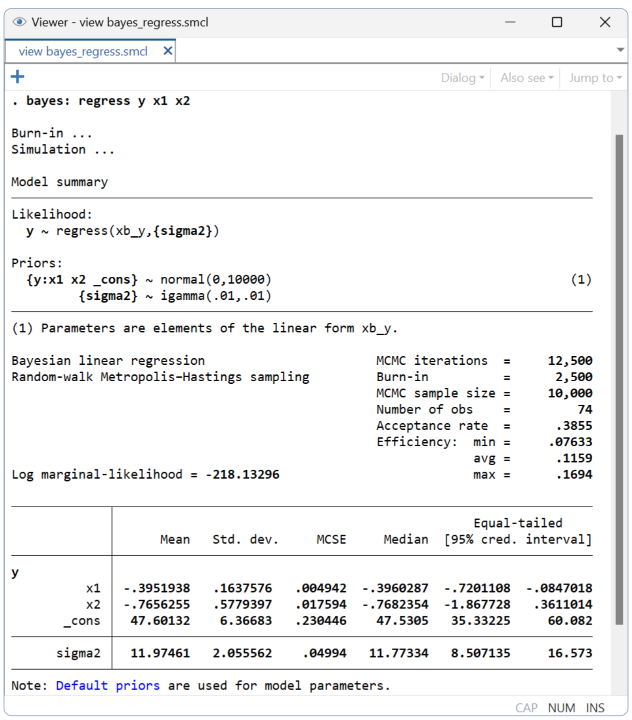
- Over 60 likelihood models supported, including multilevel, survival, GLM, VAR, DSGE, and more
- Censoring, truncation, sample selection
- Intuitive and elegant model specification
- Default and custom priors
- Comprehensive Bayesian-features support



Linear regression

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

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



Viewer - view bayes_regress.smcl

```
. 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
```

	Mean	Std. dev.	MCSE	Median	Equal-tailed [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.

Use Gibbs sampling

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

Logistic regression

Use default normal priors for coefficients

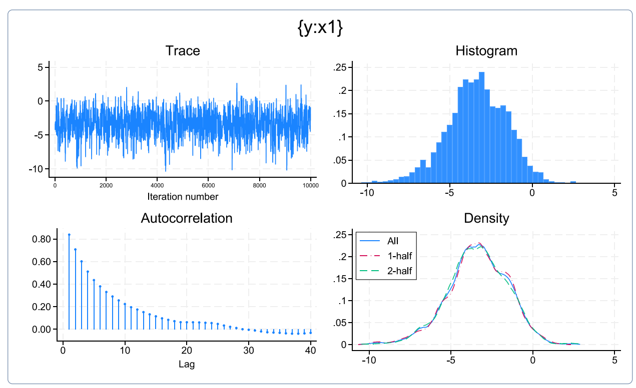
```
. bayes: logistic y x1 x2
```

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**

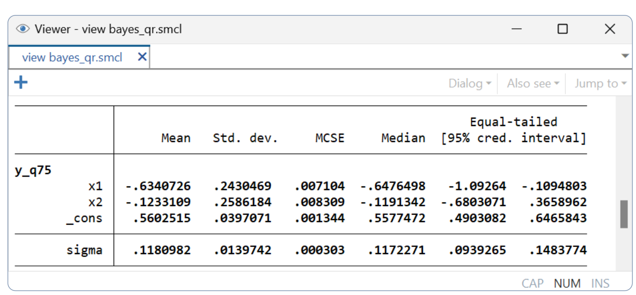
```
. bayesgraph diagnostics {y:x1}
```



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

	Mean	Std. dev.	MCSE	Median	Equal-tailed [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

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

view bayes_interval.smcl

Dialog Also see Jump to

```
. 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
-----------------------------------------------
```

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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

view bayes_ic.smcl

Dialog Also see Jump to

```
. 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.
```

CAP NUM INS

Compare models using posterior probabilities

```
. bayestest model exp weibull
```

Viewer - view bayes_model.smcl

view bayes_model.smcl

Dialog Also see Jump to

```
. 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.
```

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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

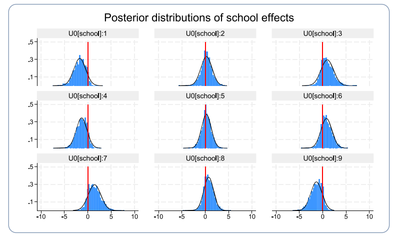
```
. bayes: ...
```

Multilevel models

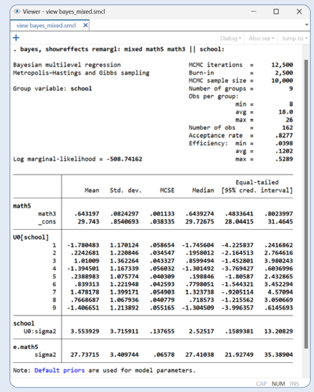
Small number of groups?

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



```
. 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

```
. 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.
```

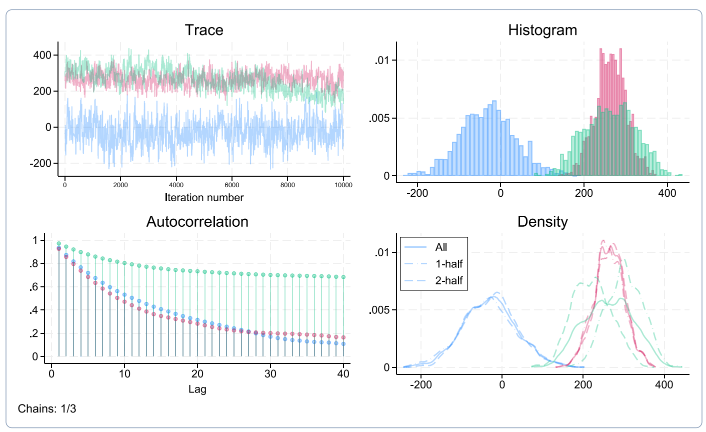
Gelman–Rubin convergence diagnostics

Check Gelman–Rubin convergence diagnostics

```
. 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
```

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

MCMC replicates

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

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

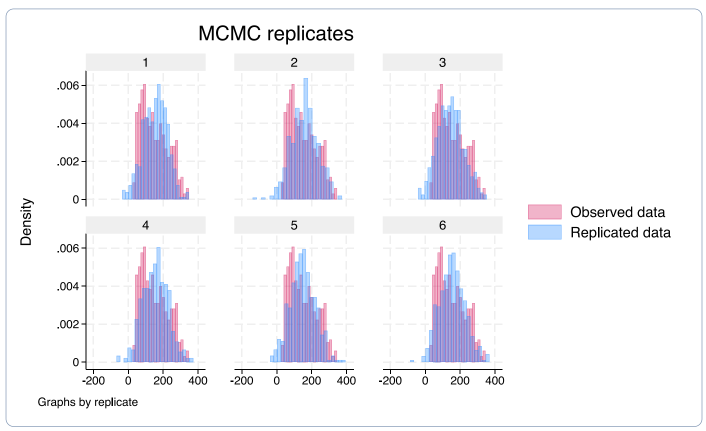
List the first 10 observations

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



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
```

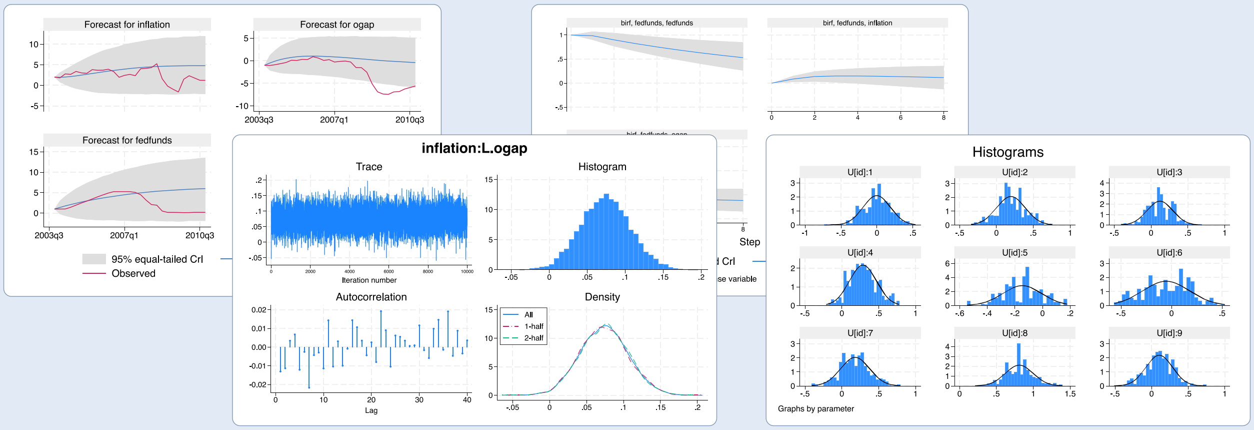
T	Mean	Std. dev.	E(T_obs)	P(T>=T_obs)
mean	3.045143	.0787588	3.044554	.5026
min	.5130189	.3401942	1.049675	.0365
max	5.84806	.3703789	5.703145	.626
skew	.1471358	.1660461	.1555046	.4806

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
```

Bayesian econometrics

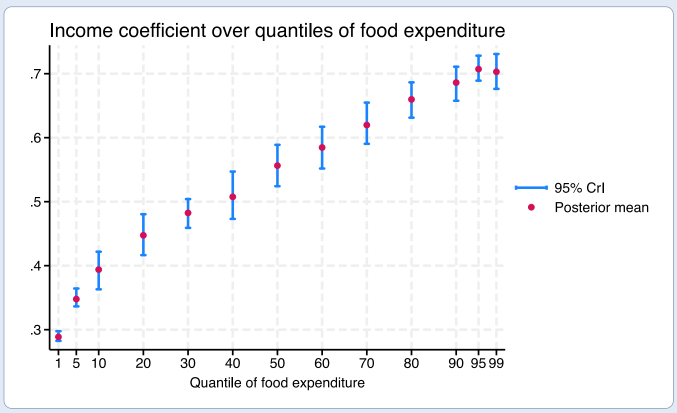


- Panel-data models
- Dynamic forecasting
- VAR models
- IRF and FEVD analysis
- Linear and nonlinear DSGE models
- And more

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



stata.com/new-in-bayesian-analysis

stata.com/bayesian-analysis