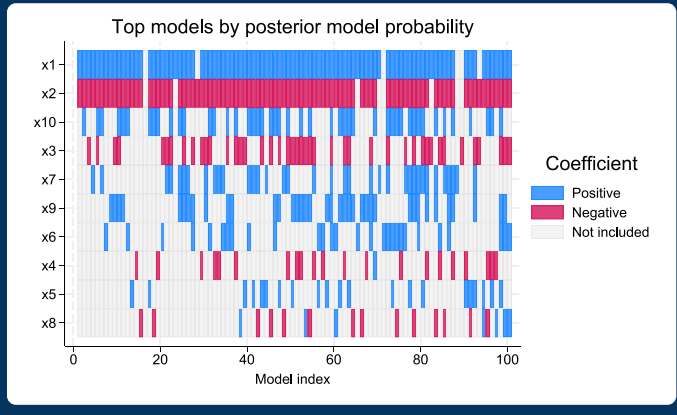
New in STATA 18

Bayesian model averaging

Uncertain which predictors to include in your regression model?
Would you like to account for this uncertainty in your anaysis?
Want to learn about influential models and important predictors?

Stata's new Bayesian model averaging (BMA) suite can help.

- Model choice, inference, and prediction
- Influential models using posterior model probabilities (PMPs)
- Important predictors using posterior inclusion probabilities (PIPs)
- Uniform, binomial, and beta-binomial model priors
- Many *g*-priors: fixed, robust, hyper-*g*, ...
- Posterior inference, including credible intervals, for coefficients and predictions
- Jointness measures for pairs of predictors
- Variable-inclusion maps
- Predictive performance using log predictive-score (LPS)
- And more



Stata's new **bma** suite performs BMA, which combines results from multiple candidate models weighted by models' probabilities given the observed data. This leads to more reliable inference and prediction that accounts for model uncertainty.

BMA workflow

Fit BMA linear regression

```
. bmaregress y x1-x100
```

Save BMA simulation results

```
. bmaregress, saving(bmamcmc)
```

Check BMA convergence

```
. bmagraph pmp
```

Identify influential models by using PMP

```
. bmastats models
```

Identify important predictors by using PIP

```
. bmastats pip x10-x20
```

Visually explore important predictors by producing variable-inclusion maps

```
. bmagraph varmap
```

Explore model-size distributions

```
. bmastats msize
. bmagraph msize
```

Simulate posterior distributions of model parameters

```
. bmacoefsample, saving(bmacoef)
```

Obtain posterior summaries of model parameters

```
. bayesstats summary
```

Plot posterior distributions of coefficients

```
. bmagraph coefdensity {x1} {x2}
```

Generate predictions and predictive credible intervals

```
. bmapredict ypmean, mean
. bmapredict y_cril y_criu, cri
```

Compare predictive performance of BMA models using LPS

```
. bmastats lps bma1 bma2 if testsample == 1
```

BMA linear regression

Fit a BMA linear regression of **y** on **x1** through **x40** to explore 2^{40} potential models. Use the default **Beta-binomial(1, 1)** model prior uniform over the model size and the **Hyper-g(3)** prior for the *g* parameter of Zellner's *g* prior. Save simulation results, specify a random-number seed for reproducibility, and display results only for predictors with a PIP of at least 0.1.

```
. bmaregress y x1-x40, gprior(hyperg 3) saving(bmamcmc) rseed(18)
  pipcutoff(0.1)

Burn-in ...
Simulation ...
Computing model probabilities ...

Bayesian model averaging                        No. of obs        =    200
Linear regression                               No. of predictors =     40
MC3 and adaptive MH sampling                              Groups  =     40
                                                          Always  =      0
                                                No. of models     =    314
                                                   For CPMP >= .9 =    130
Priors:                                         Mean model size   =  5.123
  Models: Beta-binomial(1, 1)                   Burn-in           =  2,500
   Cons.: Noninformative                        MCMC sample size  = 10,000
   Coef.: Zellner's g                           Acceptance rate   = 0.4854
       g: Hyper-g(3)
  sigma2: Noninformative                        Mean sigma2       =  1.023

Sampling correlation = 0.9207
```

y	Mean	Std. dev.	Group	PIP
x2	1.15429	.0728323	2	1
x10	-4.730936	.185496	10	1
x37	.032751	.0145241	37	.8906
x35	.0245493	.0189709	35	.6767
x22	.0258066	.0331922	22	.414
x34	.0092896	.0150387	34	.3072
x39	.0060078	.0132044	39	.1943
x40	.0026092	.0074414	40	.1289
Always				
_cons	.5235217	.0787887	0	1

```
Note: Coefficient posterior means and std. dev. estimated from 314
      models.
Note: Default prior is used for models.
Note: 32 predictors with PIP less than .1 not shown.
```

	Mean	Std. dev.	MCSE	Median	[95% cred.	interval]
g	1436.719	4472.467	119.288	857.0709	300.7584	5156.588
Shrinkage	.9986692	.000813	.000027	.9988346	.9966861	.9998061

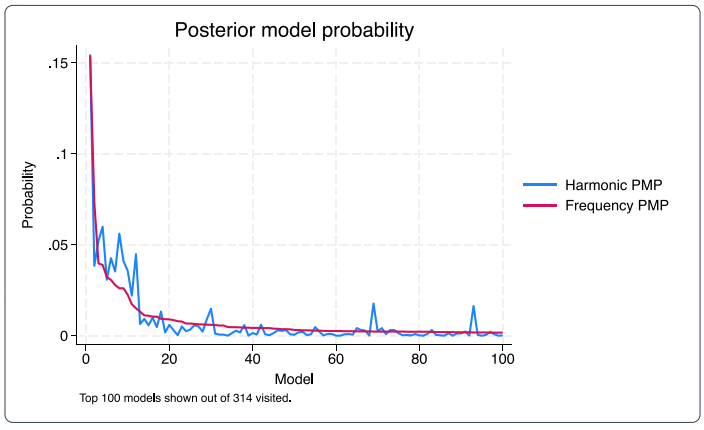
bmaregress explored 314 models with an average model size of 5.123. Predictors **x2** and **x10** with PIPs of 1 were included in essentially all considered models. And roughly 90% of the models included predictor **x37**. There are also 32 predictors with a PIP less than 0.1, which are not shown in the output.

Because we specified a random prior for the *g* parameter, we also see the posterior summaries for it and the shrinkage parameter, which is $g/(g + 1)$. The shrinkage is close to 1, so there is little shrinkage of coefficients toward 0 in this model.

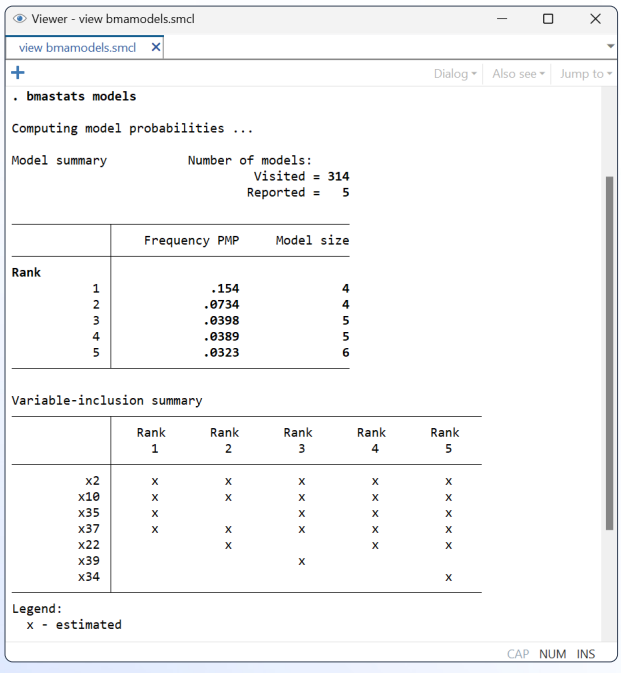
Posterior model probabilities (PMPs)

Check BMA convergence, and explore the number of models with high PMP

```
. bmagraph pmp
```



Explore influential models ranked by their PMPs



By default, **bmastats models** shows the top 5 models ranked by their PMP, but we can specify the **top()** option to see more models. The model with the highest PMP of 0.154 includes the predictors **x2**, **x10**, **x35**, and **x37**. The model with the next-highest PMP of 0.0734 includes all the same predictors, except that **x22** is included instead of **x35**. The remaining listed models have similar PMPs below 0.05.

Posterior inclusion probabilities (PIPs)

Identify important predictors

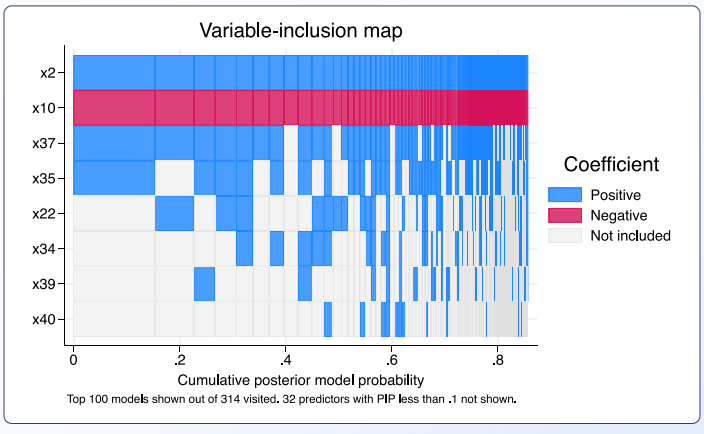
```
. bmastats pip, pipcutoff(0.5)

Posterior inclusion probability (PIP)

No. of obs          =   200
No. of predictors   =    40
            Groups  =    40
            Always  =     0
          Reported  =     4
No. of models       =   314
Mean model size     = 5.123
```

	PIP	Group
x2	1	2
x10	1	10
x37	.8906	37
x35	.6767	35
Always		
_cons	1	0

Note: Using frequency PMPs.
Note: 36 predictors with PIP less than .5 not shown.

Variable-inclusion maps

```
. bmagraph varmap, pipcutoff(0.1)
```



Jointness measures

Explore jointness for pairs of predictors

```
. bmastats jointness x37 x22

Variables: x37 x22
```

	Jointness
Doppelhofer–Weeks	.8903163
Ley–Steel type 1	.4228378
Ley–Steel type 2	.7326153
Yule's Q	.4179109
Modified Yule's Q	.4173874

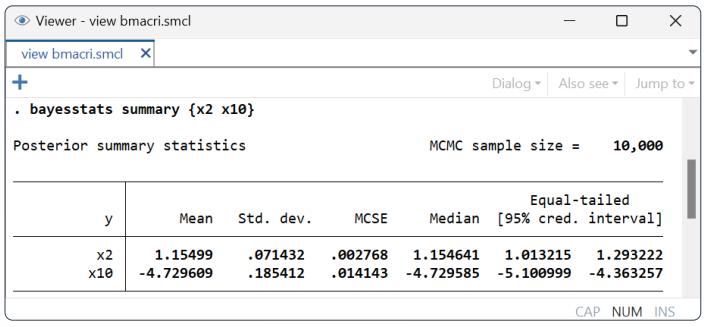
Notes: Using frequency PMPs. See thresholds

Posterior summaries: Credible intervals

Simulate posterior distributions of model parameters, including regression coefficients

```
. bmacoefsample, saving(coefmcmc) rseed(18)
```

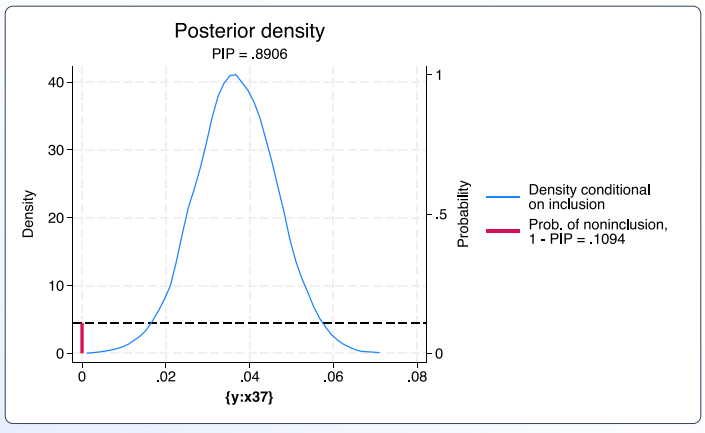
Obtain posterior summaries, including posterior means and credible intervals



Coefficient posterior density plots

Plot posterior density for coefficient of predictor **x37**

```
. bmagraph coefdensity {x37}
```



And much more

Generate posterior predictive means

```
. bmapredict ypmean, mean
```

Generate posterior predictive credible intervals

```
. bmapredict y_cril y_criu, cri
```

Check the model's performance

```
. bmastats lps if testsample == 1
```

stata.com/bma


STATA
18