

bayestest model — Hypothesis testing using model posterior probabilities

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Description

`bayestest model` computes posterior probabilities of Bayesian models fit using the `bayesmh` command or the `bayes` prefix. These posterior probabilities can be used to test hypotheses about model parameters. The command reports marginal likelihoods, prior probabilities, and posterior probabilities for all tested models.

Quick start

Compute posterior probabilities of models corresponding to previously saved estimation results M1 and M2

```
bayestest model M1 M2
```

Same as above, but specify prior probabilities for models

```
bayestest model M1 M2, prior(0.3 0.7)
```

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Syntax

```
bayestest model [ namelist ] [ , options ]
```

where *namelist* is a name, a list of names, `_all`, or `*`. A name may be `.`, meaning the current (active) estimates. `_all` and `*` mean the same thing.

<i>options</i>	Description
Main	
<code>prior(<i>numlist</i>)</code>	specify prior probabilities for tested models; default is all models are equally likely
<code>* chains(_all <i>numlist</i>)</code>	specify which chains to use for computation; default is <code>chains(_all)</code>
<code>* sepchains</code>	compute results separately for each chain
Advanced	
<code><u>marglmethod</u>(<i>method</i>)</code>	specify marginal-likelihood approximation method; default is to use Laplace–Metropolis approximation, <code>lmetropolis</code> ; rarely used

*Options `chains()` and `sepchains` are relevant only when option `nchains()` is used with `bayesmh` or the `bayes` prefix.

`collect` is allowed; see [U] 11.1.10 Prefix commands.

<i>method</i>	Description
<code><u>lmetropolis</u></code>	Laplace–Metropolis approximation; default
<code><u>hmean</u></code>	harmonic-mean approximation

Options

Main

`prior(numlist)` specifies prior probabilities for models. By default, all models are assumed to be equally likely. You may specify probabilities for all tested models, in which case the probabilities must sum to one. Alternatively, you may specify probabilities for all but the last model, in which case the sum of the specified probabilities must be less than one, and the probability for the last model is computed as one minus this sum.

`chains(_all | numlist)` specifies which chains from the MCMC sample to use for computation. The default is `chains(_all)` or to use all simulated chains. Using multiple chains, provided the chains have converged, generally improves MCMC summary statistics. Option `chains()` is relevant only when option `nchains()` is specified with `bayesmh` or the `bayes` prefix.

`sepchains` specifies that the results be computed separately for each chain. The default is to compute results using all chains as determined by option `chains()`. Option `sepchains` is relevant only when option `nchains()` is specified with `bayesmh` or the `bayes` prefix.

Advanced

`marglmethod(method)` specifies a method for approximating the marginal likelihood. *method* is either `lmetropolis`, the default, for Laplace–Metropolis approximation or `hmean` for harmonic-mean approximation. This option is rarely used.

Remarks and examples

Remarks are presented under the following headings:

[Introduction](#)

[Testing nested hypotheses](#)

[Comparing models with different priors](#)

Introduction

In this entry, we describe hypothesis testing by computing model posterior probabilities, probabilities of Bayesian models given observed data. For interval hypothesis testing, see [\[BAYES\] bayestest interval](#).

The `bayestest model` command computes posterior probabilities for specified models. The computed probabilities can be used to compare which model is more likely among considered models given observed data. You can compare models that differ only in several covariates or models with completely different regression functions, such as linear and nonlinear models. You can compare models with different outcome distributions or with different prior distributions or both. The only requirements are that the considered models have proper posterior distributions and that the same data are used to fit the models. If MCMC is used to approximate posterior distributions, convergence of MCMC should also be verified before model comparison.

The results reported by `bayestest model` are related to Bayes factors; see [\[BAYES\] bayesstats ic](#) to compute Bayes factors.

To use `bayestest model`, you must store estimation results after each Bayesian model of interest. You can use `estimates store` (see [\[R\] estimates store](#)) to store estimation results after `bayesmh` or the `bayes` prefix, as you can with other estimation commands, provided you also saved simulation results from `bayesmh` or the `bayes` prefix using the `saving()` option. See [Storing estimation results after Bayesian estimation](#) in [\[BAYES\] Bayesian postestimation](#) for details.

Testing nested hypotheses

Consider the following Bayesian regression model for `auto.dta`,

$$\text{mpg} = \beta_0 + \beta_1 \text{weight1} + \beta_2 \text{length1} + \epsilon$$

where `weight1` and `length1` are the original `weight` and `length` variables rescaled to have similar scale as `mpg`.

We assume that errors are normally distributed: $\epsilon \sim \text{normal}(0, \sigma^2)$. We also assume a noninformative Jeffreys prior for the parameters: $(\beta, \sigma^2) \sim 1/\sigma^2$. Suppose that we are interested in testing whether there is a relationship between mileage and weight and length of cars. We will consider four models: the mean-only model, the model with weight only, the model with length only, and the full model with both covariates.

In a frequentist setting, the four models correspond to the following hypotheses: $H_0: \beta_1 = 0$, $\beta_2 = 0$, $H_0: \beta_1 = 0$, and $H_0: \beta_2 = 0$. In a Bayesian setting, we cannot formulate point hypotheses for parameters with continuous distributions; see [\[BAYES\] bayestest interval](#) for examples. However, we can compute probabilities of how likely each of the four models is given the observed data.

Let's load `auto.dta` and generate rescaled versions of `weight` and `length`.

```
. use https://www.stata-press.com/data/r18/auto
(1978 automobile data)
. generate weight1 = weight/100
. generate length1 = length/10
```

Next, we fit the four models using `bayesmh`. We use the `saving()` option to save the simulation datasets so that we can store estimation results of each model for later use with `bayestest model`.

The first model we fit is the mean-only model. We store its estimation results as `meanonly`.

```
. set seed 14
. bayesmh mpg, likelihood(normal({var}))
> prior({mpg:}, flat) prior({var}, jeffreys)
> saving(meanonly_simdata) burnin(3500)
```

```
Burn-in ...
Simulation ...
```

```
Model summary
```

```
Likelihood:
  mpg ~ normal({mpg:_cons},{var})
```

```
Priors:
  {mpg:_cons} ~ 1 (flat)
  {var} ~ jeffreys
```

```
Bayesian normal regression           MCMC iterations =    13,500
Random-walk Metropolis-Hastings sampling  Burn-in           =     3,500
                                           MCMC sample size =   10,000
                                           Number of obs     =     74
                                           Acceptance rate   =    .2627
                                           Efficiency: min   =    .105
                                           avg               =    .1064
                                           max               =    .1078
```

```
Log marginal-likelihood = -234.64617
```

		Mean	Std. dev.	MCSE	Median	Equal-tailed [95% cred. interval]	
mpg							
	_cons	21.29355	.6768607	.020887	21.28059	20.00132	22.61904
	var	34.80707	5.963995	.181615	34.23247	24.9129	47.6883

```
file meanonly_simdata.dta saved.
```

```
. estimates store meanonly
```

To accommodate the Jeffreys prior for the parameters, we specify suboption `flat` within the `prior()` option for coefficients to request the flat prior with the density of 1 and suboption `jeffreys` within `prior()` for the variance parameter to request a Jeffreys prior. We also specify a longer burn-in period to improve convergence of MCMC samples for all examples. (Remember to use `bayesgraph` to check convergence of MCMC.)

We fit the second model containing only covariate length1 and store its results as length:

```
. set seed 14
. bayesmh mpg length1, likelihood(normal({var}))
> prior({mpg:}, flat) prior({var}, jeffreys)
> saving(length_simdata) burnin(3500)
Burn-in ...
Simulation ...
Model summary
```

```
Likelihood:
  mpg ~ normal(xb_mpg,{var})
Priors:
  {mpg:length1 _cons} ~ 1 (flat) (1)
  {var} ~ jeffreys
```

(1) Parameters are elements of the linear form xb_mpg.

```
Bayesian normal regression          MCMC iterations =    13,500
Random-walk Metropolis-Hastings sampling  Burn-in           =     3,500
                                          MCMC sample size =   10,000
                                          Number of obs    =     74
                                          Acceptance rate  =    .2865
                                          Efficiency: min =    .0771
                                          avg              =    .07938
                                          max              =    .08286
```

Log marginal-likelihood = -198.7678

	Mean	Std. dev.	MCSE	Median	Equal-tailed [95% cred. interval]	
mpg						
length1	-2.069861	.1882345	.006539	-2.068094	-2.44718	-1.706264
_cons	60.20346	3.562119	.127411	60.20927	53.34306	67.22423
var	12.88852	2.273808	.081887	12.62042	9.169482	18.16685

file length_simdata.dta saved.

```
. estimates store length
```

We fit the third model containing only covariate `weight1` and store its results as `weight`:

```
. set seed 14
. bayesmh mpg weight1, likelihood(normal({var}))
> prior({mpg:}, flat) prior({var}, jeffreys)
> saving(weight_simdata) burnin(3500)
Burn-in ...
Simulation ...
Model summary
```

```
Likelihood:
  mpg ~ normal(xb_mpg,{var})
Priors:
  {mpg:weight1 _cons} ~ 1 (flat) (1)
  {var} ~ jeffreys
```

(1) Parameters are elements of the linear form `xb_mpg`.

```
Bayesian normal regression          MCMC iterations =    13,500
Random-walk Metropolis-Hastings sampling  Burn-in          =     3,500
                                          MCMC sample size =   10,000
                                          Number of obs    =     74
                                          Acceptance rate =    .1735
                                          Efficiency: min =    .0463
                                          avg             =    .06694
                                          max             =    .07989
```

Log marginal-likelihood = -198.20751

	Mean	Std. dev.	MCSE	Median	Equal-tailed [95% cred. interval]	
mpg						
weight1	-.6014409	.0506121	.001791	-.6013071	-.6996976	-.50121
_cons	39.45934	1.574673	.057646	39.49735	36.31386	42.33547
var	12.13997	2.141741	.099534	11.87332	8.883221	17.14041

file `weight_simdata.dta` saved.

```
. estimates store weight
```

Finally, we fit the last model containing both covariates and store its results as full:

```
. set seed 14
. bayesmh mpg weight1 length1, likelihood(normal({var}))
> prior({mpg:}, flat) prior({var}, jeffreys)
> saving(full_simdata) burnin(3500)
Burn-in ...
Simulation ...
Model summary
```

```
Likelihood:
  mpg ~ normal(xb_mpg,{var})
Priors:
  {mpg:weight1 length1 _cons} ~ 1 (flat)
  {var} ~ jeffreys
```

(1) Parameters are elements of the linear form xb_mpg.

```
Bayesian normal regression          MCMC iterations =    13,500
Random-walk Metropolis-Hastings sampling  Burn-in           =     3,500
                                          MCMC sample size =   10,000
                                          Number of obs     =     74
                                          Acceptance rate   =    .2323
                                          Efficiency: min   =    .05455
                                          avg               =    .06647
                                          max               =    .08085
```

Log marginal-likelihood = -196.86195

	Mean	Std. dev.	MCSE	Median	Equal-tailed [95% cred. interval]	
mpg						
weight1	-.3977027	.1580411	.005558	-.401646	-.6965175	-.0721332
length1	-.7599159	.5546754	.021944	-.7502182	-1.907818	.3106868
_cons	47.5913	6.132597	.262563	47.5656	35.89593	60.18002
var	11.81753	1.96315	.07608	11.59273	8.729182	16.14065

```
file full_simdata.dta saved.
. estimates store full
```

► Example 1: Computing posterior probabilities of models

We now use bayestest model to compute posterior probabilities of the four models.

```
. bayestest model meanonly length weight full
Bayesian model tests
```

	log(ML)	P(M)	P(M y)
meanonly	-234.6462	0.2500	0.0000
length	-198.7678	0.2500	0.1055
weight	-198.2075	0.2500	0.1848
full	-196.8619	0.2500	0.7097

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

The mean-only model is very unlikely compared with other models. The length and weight models are somewhat likely with the respective posterior probabilities of 0.11 and 0.18, and the full model has the highest posterior probability of 0.71.

▷ Example 2: Specifying prior probabilities of models

If we have some prior knowledge about each of the models, we can use the `prior()` option to specify prior probabilities for each model. For example, suppose that we have prior knowledge that the weight model is much more likely than the full model so that the prior probabilities are 0.1 for the mean-only model and the length model, 0.6 for the weight model, and only 0.2 for the full model.

```
. bayestest model meanonly length weight full, prior(0.1 0.1 0.6 0.2)
Bayesian model tests
```

	log(ML)	P(M)	P(M y)
meanonly	-234.6462	0.1000	0.0000
length	-198.7678	0.1000	0.0401
weight	-198.2075	0.6000	0.4210
full	-196.8619	0.2000	0.5389

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

Under the specified prior, posterior probabilities of the weight and full models are now more similar: 0.42 and 0.54, respectively, but the full model is still preferable.

The above is equivalent to the following prior specification:

```
. bayestest model meanonly length weight full, prior(0.1 0.1 0.6)
(output omitted)
```

◀

Using our results, we conclude that `mpg` is related to both `weight` and `length` and would proceed with the full model.

After your analysis, remember to erase the saved simulation datasets you no longer need. For example, we erase all of them by typing

```
. erase meanonly_simdata.dta
. erase weight_simdata.dta
. erase length_simdata.dta
. erase full_simdata.dta
```

Comparing models with different priors

In the previous section, we used `bayestest model` to compare nested hypotheses about which covariates to include in the regression function. We can use `bayestest model` to compare models with not only different covariates but also different outcome distributions and priors for parameters.

We continue our analysis of `auto.dta`, but for simplicity, we now consider the mean-only model for `mpg`. Let's compare models with two slightly different informative priors. We use an informative normal–inverse-gamma prior for both models,

$$(\beta_0 | \sigma^2) \sim N(\mu_0, \sigma^2/n_0)$$

$$\sigma^2 \sim \text{InvGamma}(\nu_0/2, \nu_0\sigma_0^2/2)$$

with $\mu_0 = 25$, $n_0 = 10$, and $\sigma_0^2 = 30$, but we consider two different values for the degrees of freedom: $\nu_0 = 5$ and $\nu_0 = 1$.

We use `bayesmh` to fit our models. Following the formulas, we specify a `normal()` prior for the constant `{mpg:_cons}` (mean parameter) and an inverse-gamma prior `igamma()` for the variance parameter `{var}`. We specify an expression for the variance of the normal prior distribution in parentheses.

We fit the first model with $\nu_0 = 5$ and store its estimation results as `informative1`.

```
. set seed 14
. bayesmh mpg, likelihood(normal({var}))
> prior({mpg:_cons}, normal(25,{var}/10))
> prior({var}, igamma(2.5,75)) saving(inf1_simdata)
Burn-in ...
Simulation ...
Model summary
```

```
Likelihood:
  mpg ~ normal({mpg:_cons},{var})
Priors:
  {mpg:_cons} ~ normal(25,{var}/10)
  {var} ~ igamma(2.5,75)
```

```
Bayesian normal 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  =    .2548
                                           Efficiency:      min =    .09065
                                           avg             =    .1049
                                           max             =    .1192

Log marginal-likelihood = -238.55856
```

	Mean	Std. dev.	MCSE	Median	Equal-tailed [95% cred. interval]	
mpg						
_cons	21.71853	.6592655	.019091	21.69554	20.44644	23.04896
var	35.47405	5.823372	.193417	34.72454	25.84419	48.228

```
file inf1_simdata.dta saved.
. estimates store informative1
```

We fit the second model with $\nu_0 = 1$ and store its estimation results as `informative2`.

```
. set seed 14
. bayesmh mpg, likelihood(normal({var}))
> prior({mpg:}, normal(25,{var}/10))
> prior({var}, igamma(0.5,15)) saving(inf2_simdata)
Burn-in ...
Simulation ...
Model summary
```

```
Likelihood:
  mpg ~ normal({mpg:_cons},{var})
Priors:
  {mpg:_cons} ~ normal(25,{var}/10)
  {var} ~ igamma(0.5,15)
```

```
Bayesian normal 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  =    .2261
                                           Efficiency: min =    .0941
                                           avg             =     .109
                                           max             =    .1239
```

```
Log marginal-likelihood = -239.4049
```

	Mean	Std. dev.	MCSE	Median	Equal-tailed [95% cred. interval]	
mpg						
_cons	21.7175	.6539814	.021319	21.7295	20.47311	23.02638
var	35.89504	6.288571	.178665	35.17056	25.86084	50.21624

```
file inf2_simdata.dta saved.
. estimates store informative2
```

► Example 3: Comparing models with informative priors

We now use `bayestest model` to compare our models with two different informative priors.

```
. bayestest model informative1 informative2
Bayesian model tests
```

	log(ML)	P(M)	P(M y)
informative1	-238.5586	0.5000	0.6998
informative2	-239.4049	0.5000	0.3002

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

Assuming that both models are equally likely a priori, the posterior probability of the `informative1` stored results, 0.70, is much higher than the probability of the `informative2` stored results, 0.3.

▷ Example 4: Comparing a model with noninformative prior

A note of caution regarding comparing models with informative and noninformative priors—models with noninformative priors will often win because they are typically in most agreement with the observed data. For models with noninformative priors, most of the information about parameters is contained in a likelihood. As such, any model with an informative prior that is not in perfect agreement with the data will not fit data as well as a model with a noninformative prior.

For example, let's fit our constant-only model using a noninformative Jeffreys prior for the parameters.

```
. set seed 14
. bayesmh mpg, likelihood(normal({var}))
> prior({mpg:}, flat) prior({var}, jeffreys)
> saving(jeffreys_simdata)
Burn-in ...
Simulation ...
Model summary
```

```
Likelihood:
  mpg ~ normal({mpg:_cons},{var})
Priors:
  {mpg:_cons} ~ 1 (flat)
  {var} ~ jeffreys
```

```
Bayesian normal 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  =     .2668
                                                         Efficiency: min =    .09718
                                                         avg             =     .1021
                                                         max             =     .1071
Log marginal-likelihood =  -234.645
```

	Mean	Std. dev.	MCSE	Median	Equal-tailed [95% cred. interval]	
mpg						
_cons	21.29222	.6828864	.021906	21.27898	19.99152	22.61904
var	34.76572	5.91534	.180754	34.18391	24.9129	47.61286

```
file jeffreys_simdata.dta saved.
. estimates store jeffreys
```

Let's now compare this model with our two informative models.

```
. bayestest model informative1 informative2 jeffreys
Bayesian model tests
```

	log(ML)	P(M)	P(M y)
informative1	-238.5586	0.3333	0.0194
informative2	-239.4049	0.3333	0.0083
jeffreys	-234.6450	0.3333	0.9723

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

The posterior probability of the Jeffreys model is 0.97.

Finally, at the end of our analysis, we erase all the simulation datasets we no longer need. We erase all of them by typing

```
. erase inf1_simdata.dta
. erase inf2_simdata.dta
. erase jeffreys_simdata.dta
```

Stored results

`bayestest model` stores the following in `r()`:

Macros

<code>r(names)</code>	names of estimation results used
<code>r(marglmethod)</code>	method for approximating marginal likelihood: <code>lmetropolis</code> or <code>hmean</code>
<code>r(chains)</code>	chains used in the computation, if <code>chains()</code> is specified

Matrices

<code>r(test)</code>	test results for models in <code>r(names)</code>
<code>r(test_chain#)</code>	matrix test for chain #, if <code>sepchains</code> is specified

Methods and formulas

Suppose we have r models M_j for $j = 1, \dots, r$ with prior probabilities $P(M_j)$ such that $\sum_{j=1}^r p(M_j) = 1$. Then, posterior probability for model J is

$$P(M_j|\mathbf{y}) = \frac{P(\mathbf{y}|M_j)P(M_j)}{P(\mathbf{y})}$$

where $P(\mathbf{y}|M_j) = m_j(y)$ is the marginal likelihood of M_j with respect to \mathbf{y} , and $P(\mathbf{y}) = \sum_{j=1}^r P(\mathbf{y}|M_j)P(M_j)$. See *Methods and formulas* in [\[BAYES\] bayesmh](#) for details about computing marginal likelihood.

With multiple chains, the `bayestest model` command uses the averaged across chains log marginal-likelihood for calculations. If the `sepchains` option is specified, the results are calculated and reported separately for each chain.

Also see

[\[BAYES\] bayes](#) — Bayesian regression models using the `bayes` prefix⁺

[\[BAYES\] bayesmh](#) — Bayesian models using Metropolis–Hastings algorithm⁺

[\[BAYES\] Bayesian estimation](#) — Bayesian estimation commands

[\[BAYES\] Bayesian postestimation](#) — Postestimation tools for `bayesmh` and the `bayes` prefix

[\[BAYES\] bayesstats ic](#) — Bayesian information criteria and Bayes factors

[\[BAYES\] bayesstats summary](#) — Bayesian summary statistics

[\[BAYES\] bayestest interval](#) — Interval hypothesis testing

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