

# Using bayesmixedlogit and bayesmixedlogitwtp in Stata

Matthew J. Baker  
Hunter College and the Graduate Center, CUNY

March 2, 2021

## 1 Introduction

This document presents an overview of the bayesmixedlogit and bayesmixedlogitwtp Stata packages. It mirrors closely the helpfile obtainable in Stata (i.e., through `help bayesmixedlogit` or `help bayesmixedlogitwtp`). Further background for the packages can be found in [Baker\(2014\)](#).

### 1.1 Description

bayesmixedlogit can be used to fit mixed logit models using Bayesian methods – more precisely, bayesmixedlogit produces draws from the posterior parameter distribution and then presents summary and other statistics describing the results of the drawing. Detailed analysis of the draws is left to the discretion of the user.

Implementation of bayesmixedlogit follows [Train \(2009, chap. 12\)](#), and details of how the algorithm works are described in [Baker\(2014\)](#). A diffuse prior for the mean values of the random coefficients is assumed, and the prior distribution on the covariance matrix of random coefficients is taken to be an identity inverse Wishart. bayesmixedlogit uses the Mata routines `amcmc()` (if not installed: `ssc install amcmc`) for adaptive Markov chain Monte Carlo sampling from the posterior distribution of individual level coefficients and fixed coefficients. The data setup for bayesmixedlogit is the same as for `clogit` (`ssc install clogit`). Much of the syntax follows that used by [Hole \(2007\)](#) in development of the command `mixlogit`.

### 1.2 Options

`group(varname)` specifies a numeric identifier variable for choice occasions. `group()` is required.

`identifier(varname)` identifies coefficient sets (those observations for which a set of coefficients apply). Thus, when a person is observed making choices over multiple occasions, one would use `group(varname)` to specify the choice occasions, while `identifier(varname)` would identify the person. `identifier()` is required.

`rand(varlist)` specifies independent variables with random coefficients. The variables immediately following the dependent variable in the syntax are considered to have fixed coefficients (see the examples below). While a model can be run without any independent variables with fixed coefficients, at least one random-coefficient independent variable is required for bayesmixedlogit to work. `rand()` is required.

`draws(#)` specifies the number of draws that are to be taken from the posterior distribution of the parameters. The default is `draws(1000)`.

`drawsrandom(#)` is an advanced option. The drawing algorithm treats each set of random coefficients as a Gibbs step in sampling from the joint posterior distribution of parameters. In difficult, large-dimensional problems, it might be desirable to let individual Gibbs steps run for more than one draw to achieve better mixing and convergence of the algorithm.

`drawsfixed(#)` is a more advanced option. The drawing algorithm treats fixed coefficients as a Gibbs step in sampling from the joint posterior distribution of parameters. In difficult, large-dimensional problems, it might be desirable to let this step in Gibbs sampling run for more than a single draw. The default is `drawsfixed(1)`.

`burn(#)` specifies the length of the burn-in period; the first `#` draws are discarded upon completion of the algorithm and before further results are computed.

`thin(#)` specifies that only every `#`th draw is to be retained, so if `thin(3)` is specified, only every third draw is retained. This option is designed to help ease autocorrelation in the resulting draws, as is the option `jumble`, which randomly mixes draws. Both options may be applied.

`araterandom(#)` specifies the desired acceptance rate for random coefficients and should be a number between zero and one. Because an adaptive acceptance-rejection method is used to sample random coefficients, by specifying the desired acceptance rate, the user has some control over adaptation of the algorithm to the problem. The default is `araterandom(.234)`.

`aratefixed(#)` specifies the desired acceptance rate for fixed coefficients and works in the same fashion as `araterandom(#)`.

`samlerrandom(string)` specifies the type of sampler that is to be used when random parameters are drawn. It may be set to either `global` or `mwg`. The default is `samlerrandom(global)`, which means that proposed changes to random parameters are drawn all at once. If `mwg` – an acronym for “Metropolis within Gibbs” – is instead chosen, each random parameter is drawn separately as an independent step conditional on other random parameters in a nested Gibbs step. `mwg` might be useful in situations in which initial values are poorly scaled. The workings of these options are described in greater detail in [Baker\(2014\)](#).

`samplerfixed(string)` specifies the type of sampler that is used when fixed parameters are drawn. Options are exactly as those described under `samlerrandom(string)`.

`dampparmfixed(#)` works exactly as option **`dampparmrandom(#)`** but is applied to drawing fixed parameters.

`dampparmrandom(#)` is a parameter that controls how aggressively the proposal distributions for random parameters are adapted as drawing continues. If the parameter is set close to one, adaptation is aggressive in its early phase of trying to achieve the acceptance rate specified in `araterandom(#)`. If the parameter is set closer to zero, adaptation is more gradual.

**`from(rowvector)` specifies a row vector of starting values for all parameters in order. If these are not specified, starting values are obtained via estimation of a conditional logit model via `clogit**`.**

`fromvariance(matrix)` specifies a matrix of starting values for the random parameters.

`jumble` specifies to randomly mix draws.

`noisy` specifies that a dot be produced every time a complete pass through the algorithm is finished. After 50 iterations, a function value `ln_fc(p)` will be produced, which gives the joint log of

the value of the posterior choice probabilities evaluated at the latest parameters. While `ln_fc(p)` is not an objective function per se, the author has found that drift in the value of this function indicates that the algorithm has not yet converged or has other problems.

`saving(filename)` specifies a location to store the draws from the distribution. The file will contain just the draws after any burn-in period or thinning of values is applied.

**replace** specifies that an existing file is to be overwritten.

**append** specifies that an existing file is to be appended, which might be useful if multiple runs need to be combined.

`indsave(filename)` specifies a file to which individual-level random parameters are to be saved. More precisely, `indsave(filename)` saves the draws of the individual-level parameters. Caution: For long runs and models with large numbers of individuals, specifying this option can cause memory problems. Users should be careful how it is used and consult some of the examples before employing the option.

`indkeep(#)` is for use with `indsave` and specifies that only the last # draws of the individual-level random parameters be kept. This helps avoid excessive memory consumption.

`indwide` is for use with `indsave` and affords the user a degree of control over how individual-level parameters are saved. By default, individual-level parameters are saved in a panel form, meaning that each random parameter draw is saved in a row, where draws are marked by the group identifier. If instead the user would prefer that each row contain draws of each parameter, one could specify the `indwide` option, which saves all draws in a single row, with the first entry of the row being the group identifier. By analogy with `reshape`, by default draws are saved in “long” format, whereas `indwide` stores the draws in “wide” format.

`replaceind` functions in the same way as `replace`, but in reference to the file specified in `indsave`.

`appendind` functions in the same way as `append`, but in reference to the file specified in `indsave`.

## 1.3 Examples

### 1.3.1 Example 1

A single random coefficient, one decision per group. The random parameter acceptance rate is set to 0.4, and a total of 4,000 draws are taken. The first 1,000 draws are dropped, and then every fifth draw is retained. Draws are saved as `choice_draws.dta`:

```
[1]: webuse choice
      describe
```

Contains data from <http://www.stata-press.com/data/r14/choice.dta>

```
obs:      885
vars:      7                      2 Dec 2014 13:25
size:     9,735
```

```
-----
               storage   display   value
```

variable name	type	format	label	variable label
id	int	%9.0g		
sex	byte	%9.0g	sex	
income	float	%9.0g		income in thousands
car	byte	%9.0g	nation	nationality of car
size	byte	%9.0g		
choice	byte	%9.0g		ID's chosen car
dealer	byte	%9.0g		number of dealers of each nationality in ID's city

Sorted by: id

```
[2]: bayesmixedlogit choice, rand(dealer) group(id) id(id) ///
      draws(4000) burn(1000) thin(5) arater(.4) saving(choice_draws) replace
```

Bayesian Mixed Logit Model	Observations	=	885
	Groups	=	295
Acceptance rates:	Choices	=	295
Fixed coefs	Total draws	=	4000
Random coefs(ave,min,max)= 0.239, 0.186, 0.285	Burn-in draws	=	1000
	*One of every 5 draws kept		

	choice	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
Random							
	dealer	.2150072	.0360706	5.96	0.000	.1441673	.2858471
Cov_Random							
	var_dealer	.1024538	.0322976	3.17	0.002	.0390238	.1658839

Draws saved in choice\_draws.dta

Attention!

\*Results are presented to conform with Stata covention, but  
are summary statistics of draws, not coefficient estimates.

### 1.3.2 Example 2

Fitting a mixed logit model using bayesmixedlogit, using the methods as described in [Long and Freese \(2006, sec. 7.2.4\)](#). The data must first be rendered into the correct format, which can be done using the command case2alt, which is part of the package spost9\_ado; if not installed, type net install spost9\_ado, from(<https://jslsoc.siteshost.iu.edu/stata>) from the Stata prompt. The example first arranges the data and then generates and summarizes posterior draws from a mixed logit model. The model uses bangladesh.dta, which has information on contraceptive

choice by a series of families. Coefficients of explanatory variables vary at the district level.

```
[3]: webuse choice
      describe
```

Contains data from <http://www.stata-press.com/data/r14/choice.dta>

```
obs:      885
vars:      7                      2 Dec 2014 13:25
size:     9,735
```

```
-----
      storage   display   value
variable name  type      format   label      variable label
-----
id             int       %9.0g
sex            byte      %9.0g      sex
income         float     %9.0g      income in thousands
car            byte      %9.0g      nation      nationality of car
size           byte      %9.0g
choice         byte      %9.0g      ID's chosen car
dealer         byte      %9.0g      number of dealers of each
                                   nationality in ID's city
-----
```

Sorted by: id

```
[4]: webuse bangladesh, clear
      case2alt, casevars(urban age) choice(c_use) gen(choice)
```

(Bangladesh Fertility Survey, 1989)

(note: variable `_id` used since `case()` not specified)

(note: variable `_altnum` used since `altnum()` not specified)

choice indicated by: choice

case identifier: `_id`

case-specific interactions: no\* yes\*

```
[5]: bayesmixedlogit choice, rand(yesXurban yesXage yes) group(_id) id(district) ///
      draws(10000) burn(5000) saving(bdesh_draws) replace
```

Bayesian Mixed Logit Model	Observations	=	3868
	Groups	=	60
Acceptance rates:	Choices	=	1934
Fixed coefs	Total draws	=	10000

Random coefs(ave,min,max)= 0.310, 0.231, 0.354      Burn-in draws      =      5000

choice	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
-----+-----						
Random						
yesXurban	.7796584	.1905085	4.09	0.000	.4061781	1.153139
yesXage	.0067593	.0329065	0.21	0.837	-.0577519	.0712706
yes	-.7777077	.1154274	-6.74	0.000	-1.003996	-.5514193
-----+-----						
Cov_Random						
var_yesXurban	.9302604	.4088646	2.28	0.023	.1287065	1.731814
cov_yesXurb~e	-.0010909	.034572	-0.03	0.975	-.0688672	.0666853
cov_yesXurb~s	-.3946547	.225488	-1.75	0.080	-.8367101	.0474007
var_yesXage	.0611443	.0120586	5.07	0.000	.0375042	.0847844
cov_yesXage~s	.0051727	.0258404	0.20	0.841	-.0454859	.0558313
var_yes	.5352136	.1687242	3.17	0.002	.2044401	.8659871
-----+-----						

Draws saved in bdesd\_draws.dta

Attention!

\*Results are presented to conform with Stata covention, but  
are summary statistics of draws, not coefficient estimates.

Suppose one wished to save some values of individual-level random parameters, but that the problem has too many individuals or requires too many draws to get to convergence. A useful approach in these circumstances is to complete a long first run without saving parameters, and then do a short second one using starting values. Suppose that the code in the previous example has been run. One can then run something to the effect of the following to get individual parameters:

```
[6]: mat b = e(b)
      mat beta = b[1, 1..3]
      mat V = b[1,4], b[1,5], b[1,6] \ b[1,5], b[1,7], b[1,8] \ b[1,6], b[1,7], b[1,9]

[7]: bayesmixedlogit choice, rand(yesXurban yesXage yes) group(_id) id(district) ///
      from(beta) fromv(V) draws(100) indsave(randpars) indkeep(50) replaceind
```

Bayesian Mixed Logit Model      Observations      =      3868  
Groups      =      60  
Acceptance rates:      Choices      =      1934  
Fixed coefs      =      Total draws      =      100  
Random coefs(ave,min,max)= 0.297, 0.160, 0.400      Burn-in draws      =      0

choice	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
-----+-----						
Random						
yesXurban	.7763147	.1041361	7.45	0.000	.5697116	.9829178

yesXage		.0078787	.0344768	0.23	0.820	-.0605223	.0762797
yes		-.7578993	.1074017	-7.06	0.000	-.9709811	-.5448174
-----							
Cov_Random							
var_yesXurban		.3507105	.2150101	1.63	0.106	-.0758635	.7772845
cov_yesXurb~e		-.0014138	.0203943	-0.07	0.945	-.0418756	.0390479
cov_yesXurb~s		-.1896818	.140957	-1.35	0.181	-.4693365	.0899729
var_yesXage		.0599069	.0127719	4.69	0.000	.0345679	.0852459
cov_yesXage~s		.0070305	.0200905	0.35	0.727	-.0328285	.0468896
var_yes		.3150498	.1372705	2.30	0.024	.042709	.5873906

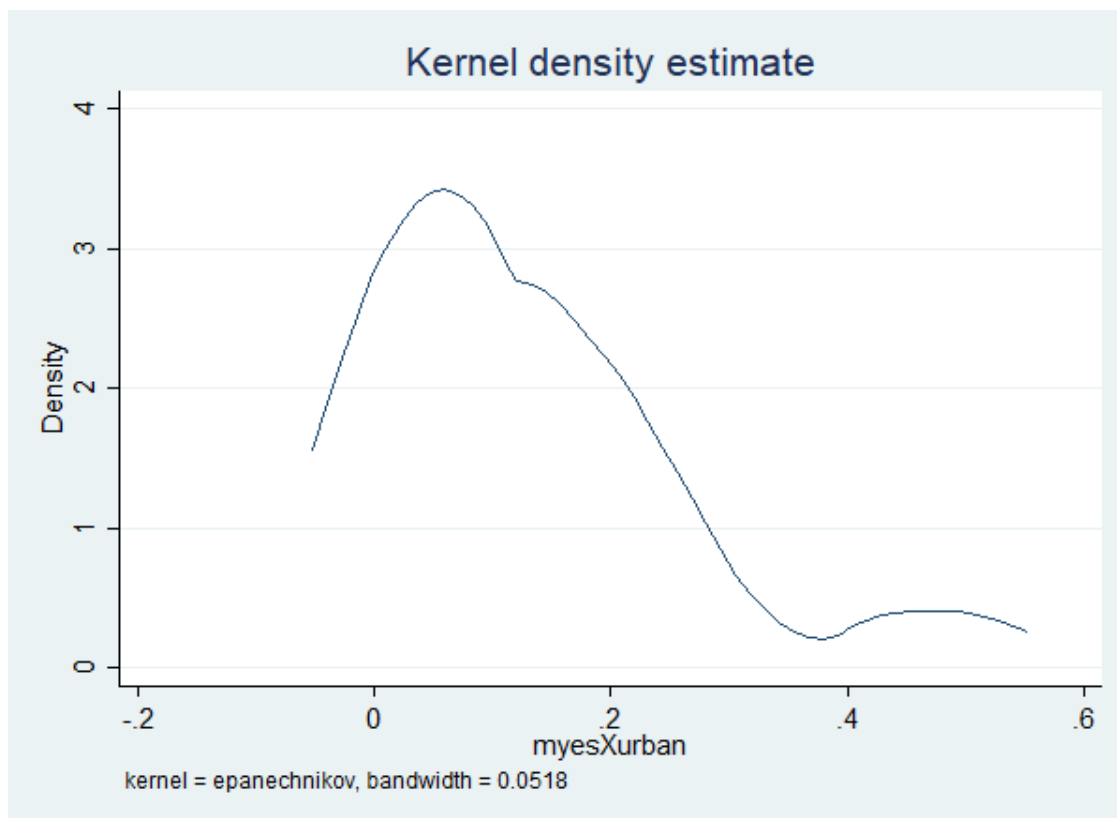
50 value(s) of individual-level random parameters saved in randpars.dta

Attention!

\*Results are presented to conform with Stata covention, but  
are summary statistics of draws, not coefficient estimates.

One post-estimation idea is to get the mean for parameter values by individuals, and fit some kernel density to the means to view the distribution of the individual-level parameters:

```
[8]: bysort district: egen myesXurban = mean(yesXurban)
      bysort district: gen last = _n == _N
      kdensity myesXurban if last
      graph display
```



```
.      global stata_kernel_graph_counter = $stata_kernel_graph_counter + 1
```

### 1.3.3 Example 3

Of course, it is possible to just do one run and retain all the information. As one final example:

```
[9]: webuse union, clear
      case2alt, casevars(age grade) choice(union) gen(unionmember)
      bayesmixedlogit unionmember, rand(y0Xage y0Xgrade y0) group(_id) id(idcode) ///
          draws(1000) burn(800) saving(parm_draws) indsave(indparm_draws) indkeep(20)
      →replaceind replace
```

(NLS Women 14-24 in 1968)

(note: variable \_id used since case() not specified)

(note: variable \_altnum used since altnum() not specified)

choice indicated by: unionmember

case identifier: \_id

case-specific interactions: y0\* y1\*

Bayesian Mixed Logit Model	Observations	=	52400
	Groups	=	4434
Acceptance rates:	Choices	=	26200
Fixed coefs	Total draws	=	1000
Random coefs(ave,min,max)= 0.221, 0.017, 0.339	Burn-in draws	=	800

unionmember	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
Random					
y0Xage	.0427559	.0045651	9.37	0.000	.033754 .0517578
y0Xgrade	-.0475095	.0097271	-4.88	0.000	-.0666903 -.0283288
y0	2.405118	.0067917	354.13	0.000	2.391726 2.418511
Cov_Random					
var_y0Xage	.0472717	.0030153	15.68	0.000	.0413258 .0532176
cov_y0Xagey~e	-.084886	.0067274	-12.62	0.000	-.0981517 -.0716203
cov_y0Xagey0	-.0017989	.0019461	-0.92	0.356	-.0056365 .0020387
var_y0Xgrade	.2070458	.0164691	12.57	0.000	.1745704 .2395211



cov_y0Xgrad~0		-.0031688	.0034891	-0.91	0.365	-.010049	.0037114
var_y0		.0808648	.0067269	12.02	0.000	.0676001	.0941296

-----

Draws saved in parm\_draws.dta  
 20 value(s) of individual-level random parameters saved in indparm\_draws.dta

Attention!

\*Results are presented to conform with Stata covention, but  
 are summary statistics of draws, not coefficient estimates.

### 1.3.4 Stored results

bayesmixedlogit stores the following in e():

**Scalars** e(N) number of observations

e(df\_r) degrees of freedom for summarizing draws (equal to number of retained draws)

e(krnd) number of random parameters

e(kfix) number of fixed parameters

e(draws) number of draws

e(burn) burn-in observations

e(thin) thinning parameter

e(random\_draws) number of draws of each set of random parameters per pass

e(fixed\_draws) number of draws of fixed parameters per pass

e(damper\_fixed) damping parameter – fixed parameters

e(damper\_random) damping parameter – random parameters

e(opt\_arate\_fixed) desired acceptance rate – fixed parameters

e(opt\_arate\_random) desired acceptance rate – random parameters

e(N\_groups) number of groups

e(N\_choices) number of choice occasions

e(arates\_fa) acceptance rate – fixed parameters

e(arates\_ra) average acceptance rate – random parameters

e(arates\_rmax) maximum acceptance rate – random parameters

e(arates\_rmin) minimum acceptance rate – random parameters

e(inddraws) draws of individual parameters kept

**Macros**   `e(cmd)` bayesmixedlogit

`e(depvar)` name of dependent variable

`e(indepvars)` independent variables

`e(title)` title in estimation output

`e(properties)` `b V`

`e(saving)` file containing results

`e(fixed_sampler)` sampler type for fixed parameters

`e(random_sampler)` sampler type for random parameters

`e(random)` random parameter names

`e(fixed)` fixed parameter names

`e(identifier)` identifier for individuals

`e(group)` identifier for choice occasions

`e(indsave)` file holding individual-level parameter draws

**Matrices**   `e(b)` mean parameter values

`e(V)` variance-covariance matrix of parameters

`e(V_init)` initial variance-covariance matrix of random parameters

`e(b_init)` initial mean vector of random parameters

`e(arates_fixed)` row vector of acceptance rates of fixed parameters

`e(arates_rand)` vector or matrix of acceptance rates of random parameters

**Functions**   `e(sample)` marks estimation sample

## 1.4 bayesmixedlogitwtp

`bayesmixedlogitwtp` is essentially a wrapper for `bayesmixedlogit`, with a transformation of the coefficient on a price variable. The defining characteristic of the WTP-space mixed logit model is normalization of coefficients using the (random) coefficient on a designated price variable, as described in [Train and Weeks \(2005\)](#), [Scarpa, Thiene, and Train \(2008\)](#), and [Hole and Kolstad \(2012\)](#).

The model assumes that the coefficient on the price variable follows (the negative of) a log-normal distribution. Hence, if the estimated parameter is  $b$ , the price variable has coefficient  $-\exp(b)$ . The transformed coefficient is saved and displayed as part of the output, but as presented the saved and display value is the negative of the exponentiated average value of  $b$ , not the average of the value  $-\exp(b)$ .

## 1.5 Options

All options for `bayesmixedlogitwtp` are the same as `bayesmixedlogit`, with the following additional option:

`price(varname)` specifies a numeric identifier variable for price occasions. `price()` is required.

### 1.5.1 Stored results

In addition to all the scalars, macros, and matrices stored by `bayesmixedlogit`, `bayesmixedlogitwtp` adds the following additional macros:

**Scalars** `e(price_coef)` - exponent of mean of estimated coefficient on price variable

**Macros** `e(pricevar)` - name of price variable

### Example 4

The following example mirrors examples provided of usage of the `mixlogitwtp` command (with thanks to Arne Rise Hole for allowing use of the example):

```
[10]: use http://fmwww.bc.edu/repec/bocode/t/traindata.dta, clear
describe

bayesmixedlogitwtp y contract local wknown, group(gid) id(pid) price(price) ///
    rand(seasonal tod) draws(4000) burn(1000) thin(5) arater(.4) saving(draws)
    →replace
```

Contains data from <http://fmwww.bc.edu/repec/bocode/t/traindata.dta>

```
obs:      4,780
vars:      9                               28 Nov 2006 18:40
size:     52,580
```

variable name	storage type	display format	value label	variable label
y	byte	%8.0g		
price	byte	%8.0g		
contract	byte	%8.0g		
local	byte	%8.0g		
wknown	byte	%8.0g		
tod	byte	%8.0g		
seasonal	byte	%8.0g		
gid	int	%8.0g		
pid	int	%9.0g		

Sorted by:

```

Bayesian Mixed Logit Model - WTP Form
Observations      =      4780
Groups            =       100
Acceptance rates:
Choices           =      1195
Fixed coefs       = 0.290
Total draws       =      4000
Random coefs(ave,min,max)= 0.214, 0.164, 0.260
Burn-in draws     =       1000
*One of every 5 draws kept

```

	y	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
-----+-----							
Fixed							
contract		-.249242	.0298574	-8.35	0.000	-.3078797	-.1906042
local		2.425951	.2125614	11.41	0.000	2.008497	2.843406
wknown		1.741476	.1599273	10.89	0.000	1.427391	2.055562
-----+-----							
Random							
price		-.3333228	.0947416	-3.52	0.000	-.5193883	-.1472574
seasonal		-9.779766	.3131075	-31.23	0.000	-10.39469	-9.164847
tod		-9.612307	.3512882	-27.36	0.000	-10.30221	-8.922403
-----+-----							
Cov_Random							
var_price		.2942746	.0795158	3.70	0.000	.1381115	.4504377
cov_pricese~l		-.2675019	.2485057	-1.08	0.282	-.7555485	.2205448
cov_pricetod		-.4965004	.2658258	-1.87	0.062	-1.018562	.0255617
var_seasonal		5.859335	1.728996	3.39	0.001	2.463715	9.254955
cov_seasona~d		4.173949	1.390441	3.00	0.003	1.443226	6.904672
var_tod		7.391194	1.994975	3.70	0.000	3.473211	11.30918

```

Draws saved in draws.dta
The price variable is price with transformed coef (-exp(b)): -0.779

```

Attention!

\*Results are presented to conform with Stata covention, but  
are summary statistics of draws, not coefficient estimates.

## 1.5.2 Example 5

A case in which all coefficients are random:

```

[11]: bayesmixedlogitwtp y, group(gid) id(pid) price(price) rand(seasonal tod wknown) /
      ↪ //
      draws(2000) burn(1000) thin(5) arater(.4) saving(draws) replace

```

```

Bayesian Mixed Logit Model - WTP Form
Observations      =      4780
Groups            =       100
Acceptance rates:
Fixed coefs       =
Random coefs(ave,min,max)= 0.152, 0.068, 0.237
Total draws       =      2000
Burn-in draws     =       1000
*One of every 5 draws kept

```

	y	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
-----+-----							
Random							
price		-.6533948	.1186226	-5.51	0.000	-.8873062	-.4194833
seasonal		-9.684424	.4084787	-23.71	0.000	-10.4899	-8.878947
tod		-9.844531	.4323386	-22.77	0.000	-10.69706	-8.992004
wknown		.9696596	.2220143	4.37	0.000	.5318704	1.407449
-----+-----							
Cov_Random							
var_price		.7395054	.2301116	3.21	0.002	.2857491	1.193262
cov_pricese~l		-.4428133	.4570225	-0.97	0.334	-1.344014	.4583876
cov_pricetod		-.4947435	.5077538	-0.97	0.331	-1.495981	.5064943
cov_pricewk~n		-.2005007	.2009999	-1.00	0.320	-.5968516	.1958502
var_seasonal		7.062787	2.070746	3.41	0.001	2.979491	11.14608
cov_seasona~d		5.437463	1.669412	3.26	0.001	2.145556	8.729371
cov_seasona~n		-.8402783	.5547666	-1.51	0.131	-1.93422	.2536639
var_tod		9.310019	2.347582	3.97	0.000	4.68083	13.93921
cov_todwknown		-1.204763	.5393129	-2.23	0.027	-2.268232	-.1412935
var_wknown		.9792376	.2518897	3.89	0.000	.4825372	1.475938

```

Draws saved in draws.dta
The price variable is price with transformed coef (-exp(b)): -0.520

```

Attention!

\*Results are presented to conform with Stata covention, but  
are summary statistics of draws, not coefficient estimates.

Looking at the distribution of draws for the price variable:

```

[12]: use draws, clear
describe
hist price
graph display

```

Contains data from draws.dta

```

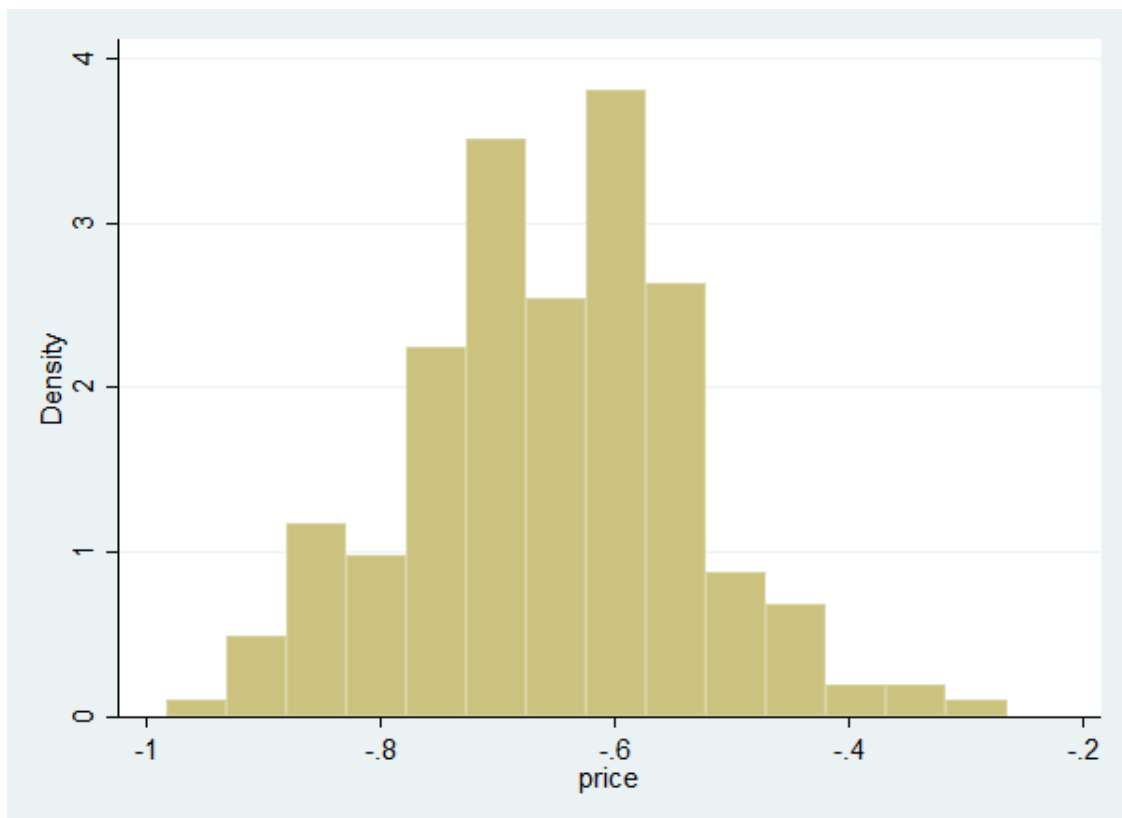
obs:      200
vars:      16
size:     12,800
1 Mar 2021 08:53

```

variable name	storage type	display format	value label	variable label
price	float	%10.0g		
seasonal	float	%10.0g		
tod	float	%10.0g		
wknown	float	%10.0g		
var_price	float	%10.0g		
cov_priceseas~l	float	%10.0g		
cov_pricetod	float	%10.0g		
cov_pricewknown	float	%10.0g		
var_seasonal	float	%10.0g		
cov_seasonaltod	float	%10.0g		
cov_seasonalw~n	float	%10.0g		
var_tod	float	%10.0g		
cov_todwknown	float	%10.0g		
var_wknown	float	%10.0g		
fun_val	float	%10.0g		
t	float	%9.0g		

Sorted by:

(bin=14, start=-.98271137, width=.05126763)



```
.      global stata_kernel_graph_counter = $stata_kernel_graph_counter + 1
```

## 1.6 References

Baker, M. J. 2014. *Adaptive Markov chain Monte Carlo sampling and estimation in Mata*. **Stata Journal** 14: 623-61.

Gelman, A., J. B. Carlin, H. S. Stern, and D. B. Rubin. 2009. **Bayesian data analysis**. 2nd. ed. Boca Raton, FL: Chapman & Hall/CRC.

Hole, A. R. 2007. *Fitting mixed logit models by using maximum simulated likelihood*. **Stata Journal** 7: 388-401.

Hole, A. R. and J. R. Kolstad. 2012. *Mixed logit estimation of willingness to pay distributions: a comparison of models in preference and WTP space using data from a health-related choice experiment*. **Empirical Economics** 42: 445-469.

Long, J. S., and J. Freese. 2006. **Regression Models for Categorical Dependent Variables Using Stata**. 2nd ed. College Station, TX: Stata Press.

R. Scarpa, M. Thiene, and K. Train. 2008. *Utility in willingness to pay space: A tool to address confounding random scale effects in destination choice to the Alps*. **American Journal of Agricultural Economics** 90: 994-1010.

Train, K. E. 2009. **Discrete Choice Methods with Simulation**. 2nd ed. Cambridge: Cambridge University Press.

Train, K. E. and M. Weeks. 2005. *Discrete choice models in preference space and willingness-to-pay space*. In: Scarpa R, Alberini A (eds), **Application of simulation methods in environmental and resource economics**. Springer, Dordrecht, pp 1-16.