asclogit — Alternative-specific conditional logit (McFadden’s choice) model

Syntax

asclogit depvar [ indepvars ] [ if ] [ in ] [ weight ], case(varname)

alternatives(varname) [ options ]

options

Model
* case(varname) use varname to identify cases
* alternatives(varname) use varname to identify the alternatives available for each case
casevars(varlist) case-specific variables
basealternative(#) | lbl | str alternative to normalize location
noconstant suppress alternative-specific constant terms
altwise use alternativewise deletion instead of casewise deletion
offset(varname) include varname in model with coefficient constrained to 1
constraints(constraints) apply specified linear constraints
collinear keep collinear variables

SE/Robust
vce(vcetype) vcetype may be oim, robust, cluster clustvar, bootstrap, or jackknife

Reporting
level(#) set confidence level; default is level(95)
or
noheader do not display the header on the coefficient table
nocnsreport do not display constraints
display_options control column formats and line width

Maximization
maximize_options control the maximization process; seldom used

coefflegend display legend instead of statistics

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*case(varname) and alternatives(varname) are required.
bootstrap, by, fp, jackknife, statsby, and xi are allowed; see [U] 11.1.10 Prefix commands.
Weights are not allowed with the bootstrap prefix; see [R] bootstrap.
fweights, iweights, and pweights are allowed (see [U] 11.1.6 weight), but they are interpreted to apply to cases
as a whole, not to individual observations. See Use of weights in [R] clogit.
coefflegend does not appear in the dialog box.
See [U] 20 Estimation and postestimation commands for more capabilities of estimation commands.
asclogit — Alternative-specific conditional logit (McFadden’s choice) model

Menu

Statistics > Categorical outcomes > Alternative-specific conditional logit

Description

asclogit fits McFadden’s choice model, which is a specific case of the more general conditional logistic regression model (McFadden 1974). asclogit requires multiple observations for each case (individual or decision), where each observation represents an alternative that may be chosen. The cases are identified by the variable specified in the case() option, whereas the alternatives are identified by the variable specified in the alternatives() option. The outcome or chosen alternative is identified by a value of 1 in depvar, whereas zeros indicate the alternatives that were not chosen. There can be multiple alternatives chosen for each case.

asclogit allows two types of independent variables: alternative-specific variables and case-specific variables. Alternative-specific variables vary across both cases and alternatives and are specified in indepvars. Case-specific variables vary only across cases and are specified in the casevars() option.

See [R] clogit for a more general application of conditional logistic regression. For example, clogit would be used when you have grouped data where each observation in a group may be a different individual, but all individuals in a group have a common characteristic. You may use clogit to obtain the same estimates as asclogit by specifying the case() variable as the group() variable in clogit and generating variables that interact the casevars() in asclogit with each alternative (in the form of an indicator variable), excluding the interaction variable associated with the base alternative. asclogit takes care of this data management burden for you. Also, for clogit, each record (row in your data) is an observation, whereas in asclogit each case, consisting of several records (the alternatives) in your data, is an observation. This last point is important because asclogit will drop observations, by default, in a casewise fashion. That is, if there is at least one missing value in any of the variables for each record of a case, the entire case is dropped from estimation. To use alternativewise deletion, specify the altwise option and only the records with missing values will be dropped from estimation.

Options

Model

case(varname) specifies the numeric variable that identifies each case. case() is required and must be integer valued.

alternatives(varname) specifies the variable that identifies the alternatives for each case. The number of alternatives can vary with each case; the maximum number of alternatives cannot exceed the limits of tabulate oneway; see [R] tabulate oneway. alternatives() is required and may be a numeric or a string variable.

casevars(varlist) specifies the case-specific numeric variables. These are variables that are constant for each case. If there are a maximum of J alternatives, there will be J − 1 sets of coefficients associated with the casevars().

basealternative(# | lbl | str) specifies the alternative that normalizes the latent-variable location (the level of utility). The base alternative may be specified as a number, label, or string depending on the storage type of the variable indicating alternatives. The default is the alternative with the highest frequency.

If vce(bootstrap) or vce(jackknife) is specified, you must specify the base alternative. This is to ensure that the same model is fit with each call to asclogit.
The `asclogit` command fits McFadden's choice model (McFadden [1974]; for a brief introduction, see Greene [2012, sec. 18.2] or Cameron and Trivedi [2010, sec. 15.5]). In this model, we have a set of unordered alternatives indexed by $1, 2, \ldots, J$. Let $y_{ij}, j = 1, \ldots, J$, be an indicator variable for the alternative actually chosen by the $i$th individual (case). That is, $y_{ij} = 1$ if individual $i$ chose alternative $j$ and $y_{ij} = 0$ otherwise. The independent variables come in two forms: alternative specific and case specific.

**Remarks and examples**

The `asclogit` command can be used with the `noconstant` option to suppress the $J - 1$ alternative-specific constant terms. The `altwise` option specifies that alternativewise deletion be used when marking out observations due to missing values in your variables. The default is to use casewise deletion; that is, the entire group of observations making up a case is deleted if any missing values are encountered. This option does not apply to observations that are marked out by the `if` or `in` qualifier or the `by` prefix.

**offset(varname)**, **constraints(numlist | matname)**, **collinear**; see [R] estimation options.

**vce(vcetype)** specifies the type of standard error reported, which includes types that are derived from asymptotic theory (`oim`), that are robust to some kinds of misspecification (`robust`), that allow for intragroup correlation (`cluster clustvar`), and that use bootstrap or jackknife methods (`bootstrap`, `jackknife`); see [R] `vce` option.

**level(#)***; see [R] estimation options.

The initial estimates must be specified as `from(matname [, copy])`, where `matname` is the matrix containing the initial estimates and the `copy` option specifies that only the position of each element in `matname` is relevant. If `copy` is not specified, the column stripe of `matname` identifies the estimates.

The following option is available with `asclogit` but is not shown in the dialog box:

**coeflegend**; see [R] estimation options.

**Remarks and examples**

The `asclogit` command fits McFadden's choice model (McFadden [1974]; for a brief introduction, see Greene [2012, sec. 18.2] or Cameron and Trivedi [2010, sec. 15.5]). In this model, we have a set of unordered alternatives indexed by $1, 2, \ldots, J$. Let $y_{ij}, j = 1, \ldots, J$, be an indicator variable for the alternative actually chosen by the $i$th individual (case). That is, $y_{ij} = 1$ if individual $i$ chose alternative $j$ and $y_{ij} = 0$ otherwise. The independent variables come in two forms: alternative specific and case specific.
specific. Alternative-specific variables vary among the alternatives (as well as cases), and case-specific variables vary only among cases. Assume that we have \( p \) alternative-specific variables so that for case \( i \) we have a \( J \times p \) matrix, \( X_i \). Further, assume that we have \( q \) case-specific variables so that we have a \( 1 \times q \) vector \( z_i \) for case \( i \). Our random-utility model can then be expressed as

\[
  u_i = X_i \beta + (z_i A)' + \epsilon_i
\]

Here \( \beta \) is a \( p \times 1 \) vector of alternative-specific regression coefficients and \( A = (\alpha_1, \ldots, \alpha_J) \) is a \( q \times J \) matrix of case-specific regression coefficients. The elements of the \( J \times 1 \) vector \( \epsilon_i \) are independent Type I (Gumbel-type) extreme-value random variables with mean \( \gamma \) (the Euler–Mascheroni constant, approximately 0.577) and variance \( \pi^2/6 \). We must fix one of the \( \alpha_j \) to the constant vector to normalize the location. We set \( \alpha_k = 0 \), where \( k \) is specified by the basealternative() option. The vector \( u_i \) quantifies the utility that the individual gains from the \( J \) alternatives. The alternative chosen by individual \( i \) is the one that maximizes utility.

Example 1

We have data on 295 consumers and their choice of automobile. Each consumer chose among an American, Japanese, or European car; the variable car indicates the nationality of the car for each alternative. We want to explore the relationship between the choice of car to the consumer’s sex (variable sex) and income (variable income in thousands of dollars). We also have information on the number of dealerships of each nationality in the consumer’s city in the variable dealer that we want to include as a regressor. We assume that consumers’ preferences are influenced by the number of dealerships in an area but that the number of dealerships is not influenced by consumer preferences (which we admit is a rather strong assumption). The variable dealer is an alternative-specific variable (\( X_i \) is a \( 3 \times 1 \) vector in our previous notation), and sex and income are case-specific variables (\( z_i \) is a \( 1 \times 2 \) vector). Each consumer’s chosen car is indicated by the variable choice.

Let’s list some of the data.

```
. use http://www.stata-press.com/data/r13/choice
. list id car choice dealer sex income in 1/12, sepby(id)

<table>
<thead>
<tr>
<th>id</th>
<th>car</th>
<th>choice</th>
<th>dealer</th>
<th>sex</th>
<th>income</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>American</td>
<td>0</td>
<td>18</td>
<td>male</td>
<td>46.7</td>
</tr>
<tr>
<td>2</td>
<td>Japan</td>
<td>0</td>
<td>8</td>
<td>male</td>
<td>46.7</td>
</tr>
<tr>
<td>3</td>
<td>Europe</td>
<td>1</td>
<td>5</td>
<td>male</td>
<td>46.7</td>
</tr>
<tr>
<td>4</td>
<td>American</td>
<td>1</td>
<td>17</td>
<td>male</td>
<td>26.1</td>
</tr>
<tr>
<td>5</td>
<td>Japan</td>
<td>0</td>
<td>6</td>
<td>male</td>
<td>26.1</td>
</tr>
<tr>
<td>6</td>
<td>Europe</td>
<td>0</td>
<td>2</td>
<td>male</td>
<td>26.1</td>
</tr>
<tr>
<td>7</td>
<td>American</td>
<td>1</td>
<td>12</td>
<td>male</td>
<td>32.7</td>
</tr>
<tr>
<td>8</td>
<td>Japan</td>
<td>0</td>
<td>6</td>
<td>male</td>
<td>32.7</td>
</tr>
<tr>
<td>9</td>
<td>Europe</td>
<td>0</td>
<td>2</td>
<td>male</td>
<td>32.7</td>
</tr>
<tr>
<td>10</td>
<td>American</td>
<td>0</td>
<td>18</td>
<td>female</td>
<td>49.2</td>
</tr>
<tr>
<td>11</td>
<td>Japan</td>
<td>1</td>
<td>7</td>
<td>female</td>
<td>49.2</td>
</tr>
<tr>
<td>12</td>
<td>Europe</td>
<td>0</td>
<td>4</td>
<td>female</td>
<td>49.2</td>
</tr>
</tbody>
</table>
```

We see, for example, that the first consumer, a male earning $46,700 per year, chose to purchase a European car even though there are more American and Japanese car dealers in his area. The fourth consumer, a female earning $49,200 per year, purchased a Japanese car.
We now fit our model.

```
. asclogit choice dealer, case(id) alternatives(car) casevars(sex income)
```

Iteration 0:  log likelihood = -273.55685
Iteration 1:  log likelihood = -252.75109
Iteration 2:  log likelihood = -250.78555
Iteration 3:  log likelihood = -250.7794
Iteration 4:  log likelihood = -250.7794

Alternative-specific conditional logit  Number of obs = 885
Case variable: id  Number of cases = 295
Alternative variable: car  Alts per case:  min = 3
                                         avg = 3.0
                                         max = 3

Wald chi2(5) = 15.86  Log likelihood = -250.7794
Prob > chi2 = 0.0072

|                | Coef.  | Std. Err. |    z   | P>|z|   | [95% Conf. Interval]        |
|----------------|--------|-----------|--------|--------|-----------------------------|
| choice         |        |           |        |        |                             |
| car            |        |           |        |        |                             |
| dealer         | .0680938 | .0344465 | 1.98   | 0.048  | .00058 .1356076            |

American  (base alternative)

Japan  
| sex    | -.5346039 | .3141564 | -1.70  | 0.089  | -1.150339 .0811314         |
| income | .0325318  | .012824  | 2.54   | 0.011  | .0073973 .0576663          |
| _cons  | -1.352189 | .6911829 | -1.96  | 0.050  | -2.706892 .002508          |

Europe  
| sex    | .5704109  | .4540247 | 1.26   | 0.209  | -.3194612 1.460283          |
| income | .032042   | .0138676 | 2.31   | 0.021  | .004862 .0592219           |
| _cons  | -2.355249 | .8526681 | -2.76  | 0.006  | -4.026448 -.6840501        |

Displaying the results as odds ratios makes interpretation easier.

```
. asclogit, or noheader
```

|                | Odds Ratio | Std. Err. |    z   | P>|z|   | [95% Conf. Interval]        |
|----------------|------------|-----------|--------|--------|-----------------------------|
| choice         |            |           |        |        |                             |
| car            |            |           |        |        |                             |
| dealer         | 1.070466   | .0368737  | 1.98   | 0.048  | 1.00058 1.145232            |

American  (base alternative)

Japan  
| sex    | .5859013  | .1840647 | -1.70  | 0.089  | .3165294 1.084513           |
| income | 1.033067  | .0132484 | 2.54   | 0.011  | 1.007425 1.059361           |
| _cons  | .2586735  | .1787907 | -1.96  | 0.050  | .0667446 1.002508           |

Europe  
| sex    | 1.769994  | .8031669 | 1.26   | 0.209  | .7265404 4.307178           |
| income | 1.032561  | .0143191 | 2.31   | 0.021  | 1.004874 1.061011           |
| _cons  | .0948699  | .0808925 | -2.76  | 0.006  | .0178376 .5045693           |

These results indicate that men (sex = 1) are less likely to pick a Japanese car over an American car than women (odds ratio 0.59) but that men are more likely to choose a European car over an American car (odds ratio 1.77). Raising a person’s income increases the likelihood that he or she
purchases a Japanese or European car; interestingly, the effect of higher income is about the same for these two types of cars.

Daniel Little McFadden was born in 1937 in North Carolina. He studied physics, psychology, and economics at the University of Minnesota and has taught economics at Pittsburgh, Berkeley, MIT, and the University of Southern California. His contributions to logit models were triggered by a student’s project on freeway routing decisions, and his work consistently links economic theory and applied problems. In 2000, he shared the Nobel Prize in Economics with James J. Heckman.

Technical note

McFadden’s choice model is related to multinomial logistic regression (see [R] mlogit). If all the independent variables are case specific, then the two models are identical. We verify this supposition by running the previous example without the alternative-specific variable, dealer.

To run mlogit, we must rearrange the dataset. mlogit requires a dependent variable that indicates the choice—1, 2, or 3—for each individual. We will use car as our dependent variable for those observations that represent the choice actually chosen.
. keep if choice == 1  
(590 observations deleted)
. mlogit car sex income

Iteration 0:  log likelihood =  -259.1712
Iteration 1:  log likelihood =  -252.81165
Iteration 2:  log likelihood =  -252.72014
Iteration 3:  log likelihood =  -252.72012
Multinomial logistic regression                           Number of obs =       295
                                   LR chi2(4)  =      12.90
                                   Prob > chi2 =     0.0118
Log likelihood =  -252.72012                          Pseudo R2 =     0.0249

           Coef. Std. Err.     z  P>|z|     [95% Conf. Interval]
------------- ----------------- ------ -------- --------------------
          car
 American     (base outcome)
          Japan
         sex  -.4694798    .3114939  -1.51  0.132   -1.079997   .1410371
       income  .0276854    .0123666   2.24  0.025    .0034472   .0519236
       _cons  -1.962651    .6216803  -3.16  0.002   -3.181122   -.7441801
          Europe
         sex   .5388443    .4525278   1.19  0.234   -.3480949   1.425783
       income  .0273670    .0137878   1.98  0.047    .0003458   .0543889
       _cons -3.180030    .7546837  -4.21  0.000  -4.659182  -1.700877

The results are the same except for the model statistic: asclogit uses a Wald test and mlogit uses a likelihood-ratio test. If you prefer the likelihood-ratio test, you can fit the constant-only model for asclogit followed by the full model and use [R] lrtest. The following example will carry this out.

. use http://www.stata-press.com/data/r13/choice, clear
. asclogit choice, case(id) alternatives(car)
. estimates store null
. asclogit choice, case(id) alternatives(car) casevars(sex income)
. lrtest null .

Technical note

We force you to explicitly identify the case-specific variables in the casevars() option to ensure that the program behaves as you expect. For example, an if or in qualifier may drop observations in such a way that (what was expected to be) an alternative-specific variable turns into a case-specific variable. Here you would probably want asclogit to terminate instead of interacting the variable with the alternative indicators. This situation could also occur if asclogit drops cases, or observations if you use the altwise option, because of missing values.
Stored results

asclogit stores the following in \textbf{e}():

Scalars
\begin{itemize}
  \item \textbf{e(N)} \quad \text{number of observations}
  \item \textbf{e(N\_case)} \quad \text{number of cases}
  \item \textbf{e(k)} \quad \text{number of parameters}
  \item \textbf{e(k\_alt)} \quad \text{number of alternatives}
  \item \textbf{e(k\_indvars)} \quad \text{number of alternative-specific variables}
  \item \textbf{e(k\_casevars)} \quad \text{number of case-specific variables}
  \item \textbf{e(k\_eq)} \quad \text{number of equations in \textbf{e(b)}}
  \item \textbf{e(k\_eq\_model)} \quad \text{number of equations in overall model test}
  \item \textbf{e(df\_m)} \quad \text{model degrees of freedom}
  \item \textbf{e(ll)} \quad \text{log likelihood}
  \item \textbf{e(N\_clust)} \quad \text{number of clusters}
  \item \textbf{e(const)} \quad \text{constant indicator}
  \item \textbf{e(i\_base)} \quad \text{base alternative index}
  \item \textbf{e(chi2)} \quad \chi^2
  \item \textbf{e(F)} \quad F \text{ statistic}
  \item \textbf{e(p)} \quad \text{significance}
  \item \textbf{e(alt\_min)} \quad \text{minimum number of alternatives}
  \item \textbf{e(alt\_avg)} \quad \text{average number of alternatives}
  \item \textbf{e(alt\_max)} \quad \text{maximum number of alternatives}
  \item \textbf{e(rank)} \quad \text{rank of \textbf{e(V)}}
  \item \textbf{e(ic)} \quad \text{number of iterations}
  \item \textbf{e(rc)} \quad \text{return code}
  \item \textbf{e(converged)} \quad 1 \text{ if converged, 0 otherwise}
\end{itemize}

Macros
\begin{itemize}
  \item \textbf{e(cmd)} \quad \textbf{asclogit}
  \item \textbf{e(cmdline)} \quad \text{command as typed}
  \item \textbf{e(depvar)} \quad \text{name of dependent variable}
  \item \textbf{e(indvars)} \quad \text{alternative-specific independent variable}
  \item \textbf{e(casevars)} \quad \text{case-specific variables}
  \item \textbf{e(case)} \quad \text{variable defining cases}
  \item \textbf{e(altvar)} \quad \text{variable defining alternatives}
  \item \textbf{e(alteqs)} \quad \text{alternative equation names}
  \item \textbf{e(alt\#)} \quad \text{alternative labels}
  \item \textbf{e(vtype)} \quad \text{weight type}
  \item \textbf{e(wexp)} \quad \text{weight expression}
  \item \textbf{e(title)} \quad \text{title in estimation output}
  \item \textbf{e(clustvar)} \quad \text{name of cluster variable}
  \item \textbf{e(offset)} \quad \text{linear offset variable}
  \item \textbf{e(chi2type)} \quad \text{Wald, type of model \chi^2 \text{ test}}
  \item \textbf{e(vce)} \quad \text{vcetype specified in \textbf{vce()}}
  \item \textbf{e(vcetype)} \quad \text{title used to label Std. Err.}
  \item \textbf{e(opt)} \quad \text{type of optimization}
  \item \textbf{e(which)} \quad \text{max or min; whether optimizer is to perform maximization or minimization}
  \item \textbf{e(ml\_method)} \quad \text{type of \textbf{ml} method}
  \item \textbf{e(user)} \quad \text{name of likelihood-evaluator program}
  \item \textbf{e(technique)} \quad \text{maximization technique}
  \item \textbf{e(datasignature)} \quad \text{the checksum}
  \item \textbf{e(datasignaturevars)} \quad \text{variables used in calculation of checksum}
  \item \textbf{e(properties)} \quad \text{b V}
  \item \textbf{e(estat\_cmd)} \quad \text{program used to implement \textbf{estat}}
  \item \textbf{e(predict)} \quad \text{program used to implement \textbf{predict}}
  \item \textbf{e(marginsnotok)} \quad \text{predictions disallowed by \textbf{margins}}
\end{itemize}
In this model, we have a set of unordered alternatives indexed by 1, 2, ..., J. Let \( y_{ij} = 1 \) if individual \( i \) chose alternative \( j \) and \( y_{ij} = 0 \) otherwise. The independent variables come in two forms: alternative specific and case specific. Alternative-specific variables vary among the alternatives (as well as cases), and case-specific variables vary only among cases. Assume that we have \( p \) alternative-specific variables so that for case \( i \) we have a \( J \times p \) matrix, \( X_i \). Further, assume that we have \( q \) case-specific variables so that we have a \( 1 \times q \) vector \( z_i \) for case \( i \). The deterministic component of the random-utility model can then be expressed as

\[
\eta_i = X_i \beta + (z_i \otimes I_J) \text{vec}(A')
\]

\[
= (X_i, z_i \otimes I_J) \begin{pmatrix} \beta \\ \text{vec}(A') \end{pmatrix}
\]

\[
= X_i^* \beta^*
\]

As before, \( \beta \) is a \( p \times 1 \) vector of alternative-specific regression coefficients, and \( A = (\alpha_1, \ldots, \alpha_J) \) is a \( q \times J \) matrix of case-specific regression coefficients; remember that we must fix one of the \( \alpha_j \) to the constant vector to normalize the location. Here \( I_J \) is the \( J \times J \) identity matrix, \text{vec()} \) is the vector function that creates a vector from a matrix by placing each column of the matrix on top of the other (see \([M-5]\) \text{vec()}\)), and \( \otimes \) is the Kronecker product (see \([M-2] \text{op}_\text{kron} \)).

We have rewritten the linear equation so that it is a form that can be used by \text{clogit}, namely, \( X_i^* \beta^* \), where

\[
X_i^* = (X_i, z_i \otimes I_J)
\]

\[
\beta^* = \begin{pmatrix} \beta \\ \text{vec}(A') \end{pmatrix}
\]

With this in mind, see \textit{Methods and formulas} in \([R] \text{clogit}\) for the computational details of the conditional logit model.

This command supports the clustered version of the Huber/White/sandwich estimator of the variance using \text{vce(robust)} and \text{vce(cluster \text{clustvar})}. See \([P] \_\text{robust} \), particularly \textit{Maximum likelihood estimators} and \textit{Methods and formulas}. Specifying \text{vce(robust)} is equivalent to specifying \text{vce(cluster casevar)}, where \text{casevar} is the variable that identifies the cases.
References


Also see

[R] asclogit postestimation — Postestimation tools for asclogit

[R] asmprobit — Alternative-specific multinomial probit regression

[R] asroprobit — Alternative-specific rank-ordered probit regression

[R] clogit — Conditional (fixed-effects) logistic regression

[R] logistic — Logistic regression, reporting odds ratios

[R] logit — Logistic regression, reporting coefficients

[R] nlogit — Nested logit regression

[R] ologit — Ordered logistic regression

[U] 20 Estimation and postestimation commands