**ologit — Ordered logistic regression**

**Description**

`ologit` fits ordered logit models of ordinal variable *depvar* on the independent variables *indepvars*. The actual values taken on by the dependent variable are irrelevant, except that larger values are assumed to correspond to “higher” outcomes.

**Quick start**

Ordinal logit model of *y* on *x1* and categorical variables *a* and *b*

```
ologit y x1 i.a i.b
```

As above, and include interaction between *a* and *b* and report results as odds ratios

```
ologit y x1 a##b, or
```

With bootstrap standard errors

```
ologit y x1 i.a i.b, vce(bootstrap)
```

Analysis restricted to cases where *catvar* = 0 using *svyset* data with replicate weights

```
svy bootstrap, subpop(if catvar==0): ologit y x1 i.a i.b
```

**Menu**

Statistics > Ordinal outcomes > Ordered logistic regression
Syntax

```
ologit depvar [ indepvars ] [ if ] [ in ] [ weight ] [ , options ]
```

<table>
<thead>
<tr>
<th>options</th>
<th>Description</th>
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<tr>
<td><strong>Model</strong></td>
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</tr>
<tr>
<td>offset(varname)</td>
<td>include varname in model with coefficient constrained to 1</td>
</tr>
<tr>
<td>constraints(constraints)</td>
<td>apply specified linear constraints</td>
</tr>
<tr>
<td><strong>SE/Robust</strong></td>
<td>vctype may be oim, robust, cluster clustvar, bootstrap, or jackknife</td>
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<td>vce(vcetype)</td>
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<td><strong>Reporting</strong></td>
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<tr>
<td>level(#)</td>
<td>set confidence level; default is level(95)</td>
</tr>
<tr>
<td>or</td>
<td>report odds ratios</td>
</tr>
<tr>
<td>nocnsreport</td>
<td>do not display constraints</td>
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<tr>
<td>display_options</td>
<td>control columns and column formats, row spacing, line width, display of omitted variables and base and empty cells, and factor-variable labeling</td>
</tr>
<tr>
<td><strong>Maximization</strong></td>
<td></td>
</tr>
<tr>
<td>maximize_options</td>
<td>control the maximization process; seldom used</td>
</tr>
</tbody>
</table>
Reporting

level(#) \text{; see [R] Estimation options.}

\text{or reports the estimated coefficients transformed to odds ratios, that is, } e^b \text{ rather than } b. \text{ Standard errors and confidence intervals are similarly transformed. This option affects how results are displayed, not how they are estimated. or may be specified at estimation or when replaying previously estimated results.}

nocnsreport \text{; see [R] Estimation options.}

display_options: noci, nopvalues, noomitted, vsquish, noemptycells, baselevels, allbaselevels, nofvlabel, fvwrap(#), fvwrapon(style), cformat(\%sfmt), pformat(\%sfmt), sformat(\%sfmt), and nolstretch \text{; see [R] Estimation options.}

Maximization

maximize_options: difficult, technique(algorithm_spec), iterate(#), [no]log, trace, gradient, showstep, hessian, showtolerance, tolerance(#), ltolerance(#), nrtolerance(#), nonrtolerance, and from(init_specs) \text{; see [R] Maximize. These options are seldom used.}

The following options are available with ologit but are not shown in the dialog box:
collinear, coeflegend \text{; see [R] Estimation options.}

Remarks and examples \text{ stata.com}

Ordered logit models are used to estimate relationships between an ordinal dependent variable and a set of independent variables. An \textit{ordinal} variable is a variable that is categorical and ordered, for instance, “poor”, “good”, and “excellent”, which might indicate a person’s current health status or the repair record of a car. If there are only two outcomes, see [R] logistic, [R] logit, and [R] probit. This entry is concerned only with more than two outcomes. If the outcomes cannot be ordered (for example, residency in the north, east, south, or west), see [R] mlogit. This entry is concerned only with models in which the outcomes can be ordered.

In ordered logit, an underlying score is estimated as a linear function of the independent variables and a set of cutpoints. The probability of observing outcome \textit{i} corresponds to the probability that the estimated linear function, plus random error, is within the range of the cutpoints estimated for the outcome:

\[ \Pr(\text{outcome}_j = i) = \Pr(\kappa_{i-1} < \beta_1 x_{1j} + \beta_2 x_{2j} + \cdots + \beta_k x_{kj} + u_j \leq \kappa_i) \]

\( u_j \) is assumed to be logistically distributed in ordered logit. In either case, we estimate the coefficients \( \beta_1, \beta_2, \ldots, \beta_k \) together with the cutpoints \( \kappa_1, \kappa_2, \ldots, \kappa_{k-1} \), where \( k \) is the number of possible outcomes. \( \kappa_0 \) is taken as \( -\infty \), and \( \kappa_k \) is taken as \( +\infty \). All of this is a direct generalization of the ordinary two-outcome logit model.

\textbf{Example 1}

We wish to analyze the 1977 repair records of 66 foreign and domestic cars. The data are a variation of the automobile dataset described in [U] 1.2.2 Example datasets. The 1977 repair records, like those in 1978, take on values “Poor”, “Fair”, “Average”, “Good”, and “Excellent”. Here is a cross-tabulation of the data:
. use https://www.stata-press.com/data/r16/fullauto  
(Automobile Models)

. tabulate rep77 foreign, chi2

<table>
<thead>
<tr>
<th>Repair Record</th>
<th>Foreign</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Domestic</td>
</tr>
<tr>
<td>Poor</td>
<td>2</td>
</tr>
<tr>
<td>Fair</td>
<td>10</td>
</tr>
<tr>
<td>Average</td>
<td>20</td>
</tr>
<tr>
<td>Good</td>
<td>13</td>
</tr>
<tr>
<td>Excellent</td>
<td>0</td>
</tr>
<tr>
<td>Total</td>
<td>45</td>
</tr>
</tbody>
</table>

Pearson chi2(4) = 13.8619  Pr = 0.008

Although it appears that foreign takes on the values Domestic and Foreign, it is actually a numeric variable taking on the values 0 and 1. Similarly, rep77 takes on the values 1, 2, 3, 4, and 5, corresponding to Poor, Fair, and so on. The more meaningful words appear because we have attached value labels to the data; see [U] 12.6.3 Value labels.

Because the chi-squared value is significant, we could claim that there is a relationship between foreign and rep77. Literally, however, we can only claim that the distributions are different; the chi-squared test is not directional. One way to model these data is to model the categorization that took place when the data were created. Cars have a true frequency of repair, which we will assume is given by $S_j = \beta_{\text{foreign}} + u_j$, and a car is categorized as “poor” if $S_j \leq \kappa_0$, as “fair” if $\kappa_0 < S_j \leq \kappa_1$, and so on:

. ologit rep77 foreign

Iteration 0:  log likelihood = -89.895098
Iteration 1:  log likelihood = -85.951765
Iteration 2:  log likelihood = -85.908227
Iteration 3:  log likelihood = -85.908161
Iteration 4:  log likelihood = -85.908161

Ordered logistic regression

Log likelihood = -85.908161

Number of obs = 66
LR chi2(1) = 7.97
Prob > chi2 = 0.0047
Pseudo R2 = 0.0444

| rep77 | Coef.  | Std. Err. | z     | P>|z|  | [95% Conf. Interval] |
|-------|--------|-----------|-------|------|----------------------|
| foreign | 1.455878  | .5308951 | 2.74  | 0.006 | .4153425 | 2.496413 |
| /cut1   | -2.765562  | .5988208 | -2.87 | 0.004 | -.933229 | -.1591895 |
| /cut2   | -.9963603  | .3217706 | -1.60 | 0.054 | -1.627019 | -.3657016 |
| /cut3   | .9426153   | .3136398 | 3.01  | 0.003 | .3278925 | 1.557338 |
| /cut4   | 3.123351   | .5423257 | 5.77  | 0.000 | 2.060412 | 4.18629 |

Our model is $S_j = 1.46 \text{foreign}_j + u_j$; the expected value for foreign cars is 1.46 and, for domestic cars, 0; foreign cars have better repair records.

The estimated cutpoints tell us how to interpret the score. For a foreign car, the probability of a poor record is the probability that $1.46 + u_j \leq -2.77$, or equivalently, $u_j \leq -4.23$. Making this calculation requires familiarity with the logistic distribution: the probability is $1/(1 + e^{-4.23}) = 0.014$. On the other hand, for domestic cars, the probability of a poor record is the probability $u_j \leq -2.77$, which is 0.059.
This, it seems to us, is a far more reasonable prediction than we would have made based on the table alone. The table showed that 2 of 45 domestic cars had poor records, whereas 1 of 21 foreign cars had poor records—corresponding to probabilities $\frac{2}{45} = 0.044$ and $\frac{1}{21} = 0.048$. The predictions from our model imposed a smoothness assumption—foreign cars should not, overall, have better repair records without the difference revealing itself in each category. In our data, the fractions of foreign and domestic cars in the poor category are virtually identical only because of the randomness associated with small samples.

Thus if we were asked to predict the true fractions of foreign and domestic cars that would be classified in the various categories, we would choose the numbers implied by the ordered logit model:

<table>
<thead>
<tr>
<th></th>
<th>Domestic</th>
<th>Foreign</th>
<th>Domestic</th>
<th>Foreign</th>
</tr>
</thead>
<tbody>
<tr>
<td>Poor</td>
<td>0.044</td>
<td>0.048</td>
<td>0.059</td>
<td>0.014</td>
</tr>
<tr>
<td>Fair</td>
<td>0.222</td>
<td>0.048</td>
<td>0.210</td>
<td>0.065</td>
</tr>
<tr>
<td>Average</td>
<td>0.444</td>
<td>0.333</td>
<td>0.450</td>
<td>0.295</td>
</tr>
<tr>
<td>Good</td>
<td>0.289</td>
<td>0.333</td>
<td>0.238</td>
<td>0.467</td>
</tr>
<tr>
<td>Excellent</td>
<td>0.000</td>
<td>0.238</td>
<td>0.043</td>
<td>0.159</td>
</tr>
</tbody>
</table>

See [R] ologit postestimation for a more complete explanation of how to generate predictions from an ordered logit model.

Technical note

Here ordered logit provides an alternative to ordinary two-outcome logistic models with an arbitrary dichotomization, which might otherwise have been tempting. We could, for instance, have summarized these data by converting the five-outcome rep77 variable to a two-outcome variable, combining cars in the average, fair, and poor categories to make one outcome and combining cars in the good and excellent categories to make the second.

Another even less appealing alternative would have been to use ordinary regression, arbitrarily labeling “excellent” as 5, “good” as 4, and so on. The problem is that with different but equally valid labelings (say, 10 for “excellent”), we would obtain different estimates. We would have no way of choosing one metric over another. That assertion is not, however, true of ologit. The actual values used to label the categories make no difference other than through the order they imply.

In fact, our labeling was 5 for “excellent”, 4 for “good”, and so on. The words “excellent” and “good” appear in our output because we attached a value label to the variables; see [U] 12.6.3 Value labels. If we were to now go back and type `replace rep77=10 if rep77==5`, changing all the 5s to 10s, we would still obtain the same results when we refit our model.

Example 2

In the example above, we used ordered logit as a way to model a table. We are not, however, limited to including only one explanatory variable or to including only categorical variables. We can explore the relationship of rep77 with any of the variables in our data. We might, for instance, model rep77 not only in terms of the origin of manufacture, but also including length (a proxy for size) and mpg:
. ologit rep77 foreign length mpg  
Iteration 0:  log likelihood = -89.895098  
Iteration 1:  log likelihood = -78.775147  
Iteration 2:  log likelihood = -78.254294  
Iteration 3:  log likelihood = -78.250719  
Iteration 4:  log likelihood = -78.250719  
Ordered logistic regression  
Number of obs = 66  
LR chi2(3) = 23.29  
Prob > chi2 = 0.0000  
Log likelihood = -78.250719  
Pseudo R2 = 0.1295  

| rep77 | Coef. | Std. Err. | z   | P>|z| | [95% Conf. Interval] |
|-------|-------|-----------|-----|------|----------------------|
| foreign | 2.896807 | .7906411 | 3.66 | 0.000 | 1.347179 - 4.446435 |
| length | .0828275 | .02272 | 3.65 | 0.000 | .0382972 - .1273579 |
| mpg    | .2307677 | .0704548 | 3.28 | 0.001 | .0926788 - .3688566 |
| /cut1  | 17.92748 | 5.551191 | 3.22 | 0.001 | 7.047344 - 28.80761 |
| /cut2  | 19.86506 | 5.59648 | 3.51 | 0.000 | 8.896161 - 30.83396 |
| /cut3  | 22.10331 | 5.708936 | 3.92 | 0.000 | 10.914 - 33.29262 |
| /cut4  | 24.69213 | 5.890754 | 4.18 | 0.000 | 13.14647 - 36.2378 |

foreign still plays a role—and an even larger role than previously. We find that larger cars tend to have better repair records, as do cars with better mileage ratings.

**Stored results**

ologit stores the following in e():

Scalars
- e(N): number of observations
- e(N_cd): number of completely determined observations
- e(k_cat): number of categories
- e(k): number of parameters
- e(k_aux): number of auxiliary parameters
- e(k_eq): number of equations in e(b)
- e(k_eq_model): number of equations in overall model test
- e(k_dv): number of dependent variables
- e(df_m): model degrees of freedom
- e(r2_p): pseudo-R-squared
- e(ll): log likelihood
- e(ll_0): log likelihood, constant-only model
- e(N_clust): number of clusters
- e(chi2): \( \chi^2 \)
- e(p): p-value for model test
- e(rank): rank of e(V)
- e(ic): number of iterations
- e(rc): return code
- e(converged): 1 if converged, 0 otherwise

Macros
- e(cmd): ologit
- e(cmdline): command as typed
- e(depvar): name of dependent variable
- e(wtype): weight type
- e(wexp): weight expression
- e(title): title in estimation output
Methods and formulas

See Long and Freese (2014, ch. 7) for a discussion of models for ordinal outcomes and examples that use Stata. Cameron and Trivedi (2005, ch. 15) describe multinomial models, including the model fit by ologit. When you have a qualitative dependent variable, several estimation procedures are available. A popular choice is multinomial logistic regression (see \texttt{R mlogit}), but if you use this procedure when the response variable is ordinal, you are discarding information because multinomial logit ignores the ordered aspect of the outcome. Ordered logit and probit models provide a means to exploit the ordering information.

There is more than one “ordered logit” model. The model fit by ologit, which we will call the ordered logit model, is also known as the proportional odds model. Another popular choice, not fit by ologit, is known as the stereotype model; see \texttt{R slogit}. All ordered logit models have been derived by starting with a binary logit/probit model and generalizing it to allow for more than two outcomes.

The proportional-odds ordered logit model is so called because, if we consider the odds \( \text{odds}(k) = \frac{P(Y \leq k)}{P(Y > k)} \), then \( \text{odds}(k_1) \) and \( \text{odds}(k_2) \) have the same ratio for all independent variable combinations. The model is based on the principle that the only effect of combining adjoining categories in ordered categorical regression problems should be a loss of efficiency in estimating the regression parameters (McCullagh 1980). This model was also described by McKelvey and Zavoina (1975) and, previously, by Aitchison and Silvey (1957) in a different algebraic form. Brant (1990) offers a set of diagnostics for the model.

Peterson and Harrell (1990) suggest a model that allows nonproportional odds for a subset of the explanatory variables. ologit does not allow this, but a model similar to this was implemented by Fu (1998).

The stereotype model rejects the principle on which the ordered logit model is based. Anderson (1984) argues that there are two distinct types of ordered categorical variables: “grouped...
continuous”, such as income, where the “type a” model applies; and “assessed”, such as extent of pain relief, where the stereotype model applies. Greenland (1985) independently developed the same model. The stereotype model starts with a multinomial logistic regression model and imposes constraints on this model.

Goodness of fit for ologit can be evaluated by comparing the likelihood value with that obtained by fitting the model with mlogit. Let $\ln L_1$ be the log-likelihood value reported by ologit, and let $\ln L_0$ be the log-likelihood value reported by mlogit. If there are $p$ independent variables (excluding the constant) and $k$ categories, mlogit will estimate $p(k-1)$ additional parameters. We can then perform a “likelihood-ratio test”, that is, calculate $-2(\ln L_1 - \ln L_0)$, and compare it with $\chi^2\{p(k-2)\}$. This test is suggestive only because the ordered logit model is not nested within the multinomial logit model. A large value of $-2(\ln L_1 - \ln L_0)$ should, however, be taken as evidence of poorness of fit. Marginally large values, on the other hand, should not be taken too seriously.

The coefficients and cutpoints are estimated using maximum likelihood as described in [R] Maximize. In our parameterization, no constant appears, because the effect is absorbed into the cutpoints.

ologit and oprobit begin by tabulating the dependent variable. Category $i = 1$ is defined as the minimum value of the variable, $i = 2$ as the next ordered value, and so on, for the empirically determined $k$ categories.

The probability of a given observation for ordered logit is

$$p_{ij} = \Pr(y_j = i) = \Pr(\kappa_{i-1} < x_j \beta + u \leq \kappa_i)$$

$$= \frac{1}{1 + \exp(-\kappa_i + x_j \beta)} - \frac{1}{1 + \exp(-\kappa_{i-1} + x_j \beta)}$$

$\kappa_0$ is defined as $-\infty$ and $\kappa_k$ as $+\infty$.

For ordered probit, the probability of a given observation is

$$p_{ij} = \Pr(y_j = i) = \Pr(\kappa_{i-1} < x_j \beta + u \leq \kappa_i)$$

$$= \Phi(\kappa_i - x_j \beta) - \Phi(\kappa_{i-1} - x_j \beta)$$

where $\Phi(\cdot)$ is the standard normal cumulative distribution function.

The log likelihood is

$$\ln L = \sum_{j=1}^{N} w_j \sum_{i=1}^{k} I_i(y_j) \ln p_{ij}$$

where $w_j$ is an optional weight and

$$I_i(y_j) = \begin{cases} 1, & \text{if } y_j = i \\ 0, & \text{otherwise} \end{cases}$$

ologit and oprobit support the Huber/White/sandwich estimator of the variance and its clustered version using vce(robust) and vce(cluster clustvar), respectively. See [P] _robust, particularly Maximum likelihood estimators and Methods and formulas.
These commands also support estimation with survey data. For details on VCEs with survey data, see [SVY] Variance estimation.

References


Also see

[R] **ologit postestimation** — Postestimation tools for ologit

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

[R] **logistic** — Logistic regression, reporting odds ratios

[R] **logit** — Logistic regression, reporting coefficients

[R] **mlogit** — Multinomial (polytomous) logistic regression

[R] **oprobit** — Ordered probit regression

[R] **slogit** — Stereotype logistic regression

[BAYES] **bayes: ologit** — Bayesian ordered logistic regression

[CM] **cmrologit** — Rank-ordered logit choice model

[CM] **cmroprobit** — Rank-ordered probit choice model

[FMM] **fmm: ologit** — Finite mixtures of ordered logistic regression models

[ME] **meologit** — Multilevel mixed-effects ordered logistic regression

[MI] **Estimation** — Estimation commands for use with mi estimate

[SVY] **svy estimation** — Estimation commands for survey data

[XT] **xtologit** — Random-effects ordered logistic models

[U] **20 Estimation and postestimation commands**