truncreg — Truncated regression

Description

truncreg fits a regression model of depvar on indepvars from a sample drawn from a restricted part of the population. Under the normality assumption for the whole population, the error terms in the truncated regression model have a truncated normal distribution, which is a normal distribution that has been scaled upward so that the distribution integrates to one over the restricted range.

Quick start

Truncated regression of y on x1 and x2 truncated below 16
   truncreg y x1 x2, ll(16)

Specify that y is truncated above 35
   truncreg y x1 x2, ul(35)

With y truncated below 17 and above 35
   truncreg y x1 x2, ll(17) ul(35)

Specify a lower truncation point that varies across observations using the variable trunc
   truncreg y x1 x2, ll(trunc)

As above, but with bootstrap standard errors using 200 replications
   truncreg y x1 x2, ll(trunc) vce(bootstrap, reps(200))

See last estimates with legend of coefficient names instead of statistics
   truncreg, coeflegend

Menu

Statistics > Linear models and related > Truncated regression
# truncreg — Truncated regression

## Syntax

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

### options

<table>
<thead>
<tr>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>noconstant</code> suppress constant term</td>
</tr>
<tr>
<td>`ll(varname</td>
</tr>
<tr>
<td>`ul(varname</td>
</tr>
<tr>
<td><code>offset(varname)</code> include <code>varname</code> in model with coefficient constrained to 1</td>
</tr>
<tr>
<td><code>constraints(constraints)</code> apply specified linear constraints</td>
</tr>
<tr>
<td><code>vce(vcetype)</code> <code>vcetype</code> may be <code>oim</code>, <code>robust</code>, <code>cluster clustvar</code>, <code>opg</code>, <code>bootstrap</code>, or <code>jackknife</code></td>
</tr>
<tr>
<td><code>level(#)</code> set confidence level; default is <code>level(95)</code></td>
</tr>
<tr>
<td><code>lrmodel</code> perform the likelihood-ratio model test instead of the default Wald test</td>
</tr>
<tr>
<td><code>nocnsreport</code> do not display constraints</td>
</tr>
<tr>
<td><code>display_options</code> 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><code>maximize_options</code> control the maximization process; seldom used</td>
</tr>
<tr>
<td><code>collinear</code> keep collinear variables</td>
</tr>
<tr>
<td><code>coeflegend</code> display legend instead of statistics</td>
</tr>
</tbody>
</table>

`indepvars` may contain factor variables; see [U] 11.4.3 Factor variables.

`depvar` and `indepvars` may contain time-series operators; see [U] 11.4.4 Time-series varlists.

`bayes`, `bootstrap`, `by`, `fmm`, `fp`, `jackknife`, `mi estimate`, `rolling`, `statsby`, and `svy` are allowed; see [U] 11.1.10 Prefix commands. For more details, see [BAYES] bayes: truncreg and [FMM] fmm: truncreg.

`vce(bootstrap)` and `vce(jackknife)` are not allowed with the `mi estimate` prefix; see [MI] mi estimate.

Weights are not allowed with the `bootstrap` prefix; see [R] bootstrap.

`aweights` are not allowed with the `jackknife` prefix; see [R] jackknife.

`vce()`, `lrmodel`, and weights are not allowed with the `svy` prefix; see [SVY] svy.

`aweights`, `fweights`, `iweights`, and `pweights` are allowed; see [U] 11.1.6 weight.

`collinear` and `coeflegend` do not appear in the dialog box.

See [U] 20 Estimation and postestimation commands for more capabilities of estimation commands.

## Options

- `noconstant`; see [R] Estimation options.

`ll(varname | #)` and `ul(varname | #)` indicate the lower and upper limits for truncation, respectively.

You may specify one or both. Observations with `depvar ≤ ll()` are left-truncated, observations with `depvar ≥ ul()` are right-truncated, and the remaining observations are not truncated. See [R] tobit for a more detailed description.
offset(varname), constraints(constraints); see [R] Estimation options.

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

level(#), lrmodel, nocnsreport; see [R] Estimation options.

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

maximize options: difficult, technique(algorithm_spec), iterate(#), [no]log, trace, gradient, showstep, hessian, showtolerance, tolerance(#), ltolerance(#), nrtolerance(#), nonrtolerance, and from(init_specs); see [R] \text{Maximize}. These options are seldom used, but you may use the \text{ltol}(#) option to relax the convergence criterion; the default is \text{1e-6} during specification searches.

Setting the optimization type to \text{technique(bhhh)} resets the default \text{vcetype} to \text{vce(opg)}.

The following options are available with \text{truncreg} but are not shown in the dialog box:

collinear, coeflegend; see [R] Estimation options.

Remarks and examples stata.com

Truncated regression fits a model of a dependent variable on independent variables from a restricted part of a population. Truncation is essentially a characteristic of the distribution from which the sample data are drawn. If \( x \) has a normal distribution with mean \( \mu \) and standard deviation \( \sigma \), the density of the truncated normal distribution is

\[
\begin{align*}
f(x \mid a < x < b) &= \frac{f(x)}{\Phi \left( \frac{b-\mu}{\sigma} \right) - \Phi \left( \frac{a-\mu}{\sigma} \right)} \\
&= \frac{1}{\sigma} \frac{\phi \left( \frac{x-\mu}{\sigma} \right)}{\Phi \left( \frac{b-\mu}{\sigma} \right) - \Phi \left( \frac{a-\mu}{\sigma} \right)}
\end{align*}
\]

where \( \phi \) and \( \Phi \) are the density and distribution functions of the standard normal distribution.

Compared with the mean of the untruncated variable, the mean of the truncated variable is greater if the truncation is from below, and the mean of the truncated variable is smaller if the truncation is from above. Moreover, truncation reduces the variance compared with the variance in the untruncated distribution.
Example 1

We will demonstrate `truncreg` with part of the Mroz dataset distributed with Berndt (1996). This dataset contains 753 observations on women’s labor supply. Our subsample is of 250 observations, with 150 market laborers and 100 nonmarket laborers.

```
. use https://www.stata-press.com/data/r16/laborsub
. describe
Contains data from https://www.stata-press.com/data/r16/laborsub.dta
obs: 250
vars: 6 25 Sep 2018 18:36

storage  display value
variable name type format label variable label

lfp byte  %9.0g  1 if woman worked in 1975
whrs int    %9.0g Wife’s hours of work
kl6 byte  %9.0g  # of children younger than 6
k618 byte  %9.0g  # of children between 6 and 18
wa byte   %9.0g Wife’s age
we byte   %9.0g Wife’s educational attainment

Sorted by:
. summarize, sep(0)
```

<table>
<thead>
<tr>
<th>Variable</th>
<th>Obs</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>lfp</td>
<td>250</td>
<td>.6</td>
<td>.4908807</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>whrs</td>
<td>250</td>
<td>799.84</td>
<td>915.6035</td>
<td>0</td>
<td>4950</td>
</tr>
<tr>
<td>kl6</td>
<td>250</td>
<td>.236</td>
<td>.5112234</td>
<td>0</td>
<td>3</td>
</tr>
<tr>
<td>k618</td>
<td>250</td>
<td>1.364</td>
<td>1.370774</td>
<td>0</td>
<td>8</td>
</tr>
<tr>
<td>wa</td>
<td>250</td>
<td>42.92</td>
<td>8.426483</td>
<td>30</td>
<td>60</td>
</tr>
<tr>
<td>we</td>
<td>250</td>
<td>12.352</td>
<td>2.164912</td>
<td>5</td>
<td>17</td>
</tr>
</tbody>
</table>

We first perform ordinary least-squares estimation on the market laborers.

```
. regress whrs kl6 k618 wa we if whrs > 0
```

```
Source | SS          | df | MS | Number of obs = 150
-------|-------------|----|----|-------------------|
Model  | 7326995.15  | 4  | 1831748.79 | Prob > F = 0.0281 |
Residual | 94793104.2 | 145 | 653745.546 | R-squared = 0.0717 |
Total | 102120099 | 149 | 685369.794 | Adj R-squared = 0.0461 |
```

```
whrs     | Coef. | Std. Err. | t     | P>|t|    | [95% Conf. Interval] |
--------|-------|-----------|-------|--------|---------------------|
kl6     | -421.4822 | 167.9734 | -2.51 | 0.013  | -753.4748 -89.48953 |
k618    | -104.4571 | 54.18616 | -1.93 | 0.056  | -211.5538 2.639668 |
wa      | -4.784917 | 9.690502 | -0.49 | 0.622  | -23.9378 14.36797 |
we      | 9.353195  | 31.23793 | 0.30  | 0.765  | -52.38731 71.0937 |
_cons   | 1629.817  | 615.1301 | 2.65  | 0.009  | 414.0371 2845.597 |
```

Now, we use `truncreg` to perform truncated regression with truncation from below zero.

```
. truncreg whrs kl6 k618 wa we, ll(0)
(note: 100 obs. truncated)
Fitting full model:
Iteration 0: log likelihood = -1205.6992
Iteration 1: log likelihood = -1200.9873
Iteration 2: log likelihood = -1200.9159
```
If we assume that our data were censored, the tobit model is

```
. tobit whrs kl6 k618 wa we, ll(0)
(output omitted)
```

Tobit regression

```
Number of obs = 250
Uncensored = 150
Limits: lower = 0
Left-censored = 100
upper = +inf
Right-censored = 0
LR chi2(4) = 23.03
Prob > chi2 = 0.0001
Log likelihood = -1367.0903
Pseudo R2 = 0.0084
```

```
whrs | Coef.  Std. Err.   t    P>|t|     [95% Conf. Interval]
----------|--------|--------|-------|------------------|------------------|
kl6       | -827.7655  214.7521 -3.85 0.000  -1250.753  -404.7781
k618      | -140.0191   74.22719 -1.89 0.060  -286.2216  186.2026
wa        | -24.97918   13.25715 -1.88 0.061  -51.0918  1.04342
we        |  103.6896   41.82629  2.48 0.014  21.30625  186.0729
_cons     |  589.0002   841.5952  0.70 0.485  -1068.651  2266.652
var(e.whrs)| 1715859     216775.7 1337864 2200650
```

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```
. tobit whrs kl6 k618 wa we, ll(0)
(output omitted)
```

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Number of obs = 250
Uncensored = 150
Limits: lower = 0
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Prob > chi2 = 0.0001
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whrs | Coef.  Std. Err.   t    P>|t|     [95% Conf. Interval]
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var(e.whrs)| 1715859     216775.7 1337864 2200650
```

Technical note

Whether truncated regression is more appropriate than the ordinary least-squares estimation depends on the purpose of that estimation. If we are interested in the mean of wife’s working hours conditional on the subsample of market laborers, least-squares estimation is appropriate. However if we are interested in the mean of wife’s working hours regardless of market or nonmarket labor status, least-squares estimates could be seriously misleading.

Truncation and censoring are different concepts. A sample has been censored if no observations have been systematically excluded but some of the information contained in them has been suppressed. In a truncated distribution, only the part of the distribution above (or below, or between) the truncation points is relevant to our computations. We need to scale it up by the probability that an observation falls in the range that interests us to make the distribution integrate to one. The censored distribution used by tobit, however, is a mixture of discrete and continuous distributions. Instead of rescaling over the observable range, we simply assign the full probability from the censored regions to the censoring points. The truncated regression model is sometimes less well behaved than the tobit model.
Davidson and MacKinnon (1993) provide an example where truncation results in more inconsistency than censoring.

Stored results

_truncreg_ stores the following in _e()_

Scalars

- _e(N)_ number of observations
- _e(N_bf)_ number of observations before truncation
- _e(chi2)_ model \( \chi^2 \)
- _e(k_eq)_ number of equations in _e(b)_
- _e(k_eq_model)_ number of equations in overall model test
- _e(k_aux)_ number of auxiliary parameters
- _e(df_m)_ model degrees of freedom
- _e(ll)_ log likelihood
- _e(ll_0)_ log likelihood, constant-only model
- _e(N_clust)_ number of clusters
- _e(sigma)_ estimate of sigma
- _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)_ _truncreg_
- _e(cmdline)_ command as typed
- _e(llopt)_ contents of _ll(), if specified
- _e(ulopt)_ contents of _ul(), if specified
- _e(depvar)_ name of dependent variable
- _e(wtype)_ weight type
- _e(wexp)_ weight expression
- _e(title)_ title in estimation output
- _e(clustvar)_ name of cluster variable
- _e(offset1)_ offset
- _e(chi2type)_ Wald or LR; type of model \( \chi^2 \) test
- _e(vce)_ \_vctype_ specified in _vce()_
- _e(vcetypetitle)_ title used to label Std. Err.
- _e(opt)_ type of optimization
- _e(which)_ max or min; whether optimizer is to perform maximization or minimization
- _e(ml_method)_ type of ml method
- _e(user)_ name of likelihood-evaluator program
- _e(technique)_ maximization technique
- _e(properties)_ _b_ _V_
- _e(predict)_ program used to implement _predict_
- _e(marginsok)_ predictions allowed by _margins_
- _e(asbalanced)_ factor variables _fvset_ as _asbalanced_
- _e(asobserved)_ factor variables _fvset_ as _asobserved_

Matrices

- _e(b)_ coefficient vector
- _e(Cns)_ constraints matrix
- _e(log)_ iteration log (up to 20 iterations)
- _e(gradient)_ gradient vector
- _e(V)_ variance–covariance matrix of the estimators
- _e(V_modelbased)_ model-based variance
- _e(means)_ means of independent variables
- _e(dummy)_ indicator for dummy variables

Functions

- _e(sample)_ marks estimation sample
Methods and formulas

Greene (2018, 918–924) and Davidson and MacKinnon (1993, 534–537) provide introductions to the truncated regression model.

Let \( y = X\beta + \epsilon \) be the model. \( y \) represents continuous outcomes either observed or not observed. Our model assumes that \( \epsilon \sim N(0, \sigma^2 I) \).

Let \( a \) be the lower limit and \( b \) be the upper limit. The log likelihood is

\[
\ln L = -\frac{n}{2} \log(2\pi \sigma^2) - \frac{1}{2\sigma^2} \sum_{j=1}^{n} (y_j - x_j\beta)^2 - \sum_{j=1}^{n} \log \left\{ \Phi \left( \frac{b - x_j\beta}{\sigma} \right) - \Phi \left( \frac{a - x_j\beta}{\sigma} \right) \right\}
\]

This command supports the Huber/White/sandwich estimator of the variance and its clustered version using \vce(robust) and \vce(cluster clustvar), respectively. See [P] _robust, particularly \textit{Maximum likelihood estimators} and \textit{Methods and formulas}.

\texttt{truncreg} also supports estimation with survey data. For details on VCEs with survey data, see [SVY] \textit{Variance estimation}.

References


Also see

[R] \texttt{truncreg postestimation} — Postestimation tools for \texttt{truncreg}

[R] \texttt{regress} — Linear regression

[R] \texttt{tobit} — Tobit regression

[Bayes] \texttt{bayes: truncreg} — Bayesian truncated regression

[FMM] \texttt{fmm: truncreg} — Finite mixtures of truncated linear regression models

[MI] \textit{Estimation} — Estimation commands for use with mi estimate

[SVY] \texttt{svy estimation} — Estimation commands for survey data

[U] \textit{20 Estimation and postestimation commands}