tobit — Tobit regression

Description

tobit fits models for continuous responses where the outcome variable is censored. Censoring limits may be fixed for all observations or vary across observations.

Quick start

Tobit regression of y on x1 and x2, specifying that y is censored at the minimum of y

        tobit y x1 x2, ll

Same as above, but where the lower-censoring limit is zero

        tobit y x1 x2, ll(0)

Same as above, but specify the lower- and upper-censoring limits

        tobit y x1 x2, ll(17) ul(34)

Same as above, but where lower and upper are variables containing the censoring limits

        tobit y x1 x2, ll(lower) ul(upper)

Menu

Statistics > Linear models and related > Censored regression > Tobit regression

Syntax

> tobit *depvar* [*indepvars*] [*if*] [*in*] [*weight*] [, *options*]

options	Description
Model	
<u>noc</u>onstant	suppress constant term
ll[(*varname* | #)]	left-censoring variable or limit
ul[(*varname* | #)]	right-censoring variable or limit
<u>off</u>set(*varname*)	include *varname* in model with coefficient constrained to 1
<u>constr</u>aints(*constraints*)	apply specified linear constraints
SE/Robust	
vce(*vcetype*)	*vcetype* may be oim, opg, <u>r</u>obust, <u>cl</u>uster *clustvar*, <u>boot</u>strap, or jackknife
Reporting	
<u>l</u>evel(#)	set confidence level; default is level(95)
nocnsreport	do not display constraints
display_options	control columns and column formats, row spacing, line width, display of omitted variables and base and empty cells, and factor-variable labeling
Maximization	
maximize_options	control the maximization process; seldom used
<u>coll</u>inear	keep collinear variables
<u>coefl</u>egend	display legend instead of statistics

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, bayesboot, bootstrap, by, collect, fmm, fp, jackknife, nestreg, rolling, statsby, stepwise, and svy are allowed; see [U] **11.1.10 Prefix commands**. For more details, see [BAYES] **bayes: tobit** and [FMM] **fmm: tobit**.

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

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

vce() 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

> ┌─── **Model** ──

noconstant; see [R] **Estimation options**.

ll[(*varname* \| #)] and ul[(*varname* \| #)] indicate the lower and upper limits for censoring, respectively. Observations with *depvar* ≤ ll() are left-censored; observations with *depvar* ≥ ul() are right-censored; and remaining observations are not censored. You do not have to specify the censoring values. If you specify ll, the lower limit is the minimum of *depvar*. If you specify ul, the upper limit is the maximum of *depvar*.

offset(*varname*), constraints(*constraints*); see [R] **Estimation options**.

SE/Robust

vce(*vcetype*) specifies the type of standard error reported, which includes types that are derived from asymptotic theory (oim, opg), 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*.

Reporting

level(*#*), 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**.

Maximization

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

The following options are available with tobit but are not shown in the dialog box:

collinear, coeflegend; see [R] **Estimation options**.

Remarks and examples

tobit fits a linear regression model for a censored continuous outcome. Censoring occurs when the dependent variable is observed only within a certain range of values. When it is not, we know only that it is either above (right-censoring) or below (left-censoring) the censoring value. Censoring differs from truncation. When the data are truncated, we do not observe either the dependent variable or the covariates; see [R] **truncreg**.

Censoring may result from study design or may be a result of how the outcome is measured. Right-censoring of data may occur, for example, in income surveys that top code the highest income category. Any respondent that earns the censoring limit or more reports only the value at the limit, and we do not know the respondent's true income. Left-censoring arises naturally when measurements are obtained from an instrument or a laboratory procedure that has a limit of detection. If we observe a value at the measurement limit, we know the true value is at the limit or below it. tobit allows the censoring limits to be the same for all observations or to vary from observation to observation.

Tobin (1958) originally conceived the tobit model as one of consumption of consumer durables where purchases were left-censored at zero. Contemporary literature treats this and similar cases as a corner solution model. See Wooldridge (2020, sec. 17.2), Long (1997, 196–210), and Maddala and Lahiri (2006, 333–336) for an introduction to the tobit model. Wooldridge (2010, chap. 17 and 19) provides an advanced treatment of censored regression models. Cameron and Trivedi (2022, chap. 19) discuss the tobit model using Stata examples.

The tobit model can be written as the latent regression model $\mathbf{y} = \mathbf{x}\boldsymbol{\beta} + \epsilon$ with a continuous outcome that is either observed or unobserved. Following Cong (2000), the observed outcome for observation i is defined as

$$y_i^* = \begin{cases} y_i & \text{if } a < y_i < b \\ a & \text{if } y_i \le a \\ b & \text{if } y_i \ge b \end{cases}$$

where a is the lower-censoring limit and b is the upper-censoring limit. The tobit model assumes that the error term is normally distributed; $\epsilon \sim N(\mathbf{0}, \sigma^2\mathbf{I})$. Depending on the problem at hand, the quantity of interest in a tobit model may be the censored outcome, y_i^*, or the uncensored outcome, y_i. In the measurement instrument scenario above, we may wish to predict the values that fall below the measurement threshold. By contrast, in the consumption of consumer durables scenario above, the latent variable is an artificial construct and the variable of interest is the observed consumer expenditure.

▷ Example 1: Constant-censoring limit

University administrators want to know the relationship between high school grade point average (GPA) and students' performance in college. `gpa.dta` contains fictional data on a cohort of 4,000 college students. College GPA (gpa2) and high school GPA (hsgpa) are measured on a continuous scale between zero and four. The outcome of interest is the student's college GPA. But, for reasons of confidentiality, GPAs below 2.0 are reported as 2.0. In other words, the outcome is censored on the left.

We believe that GPA is also a function of the logarithm of income of the student's parents (pincome) and whether or not the student participated in a study-skills program while in college (program).

```
. use https://www.stata-press.com/data/r19/gpa
(High school GPA and performance in college)

. tobit gpa2 hsgpa pincome program, ll

Refining starting values:

Grid node 0:  Log likelihood = -2551.3989

Fitting full model:

Iteration 0:  Log likelihood = -2551.3989
Iteration 1:  Log likelihood = -2065.4023
Iteration 2:  Log likelihood = -2015.8135
Iteration 3:  Log likelihood = -2015.1281
Iteration 4:  Log likelihood = -2015.1258
Iteration 5:  Log likelihood = -2015.1258
```

```
Tobit regression                               Number of obs    =     4,000
                                                 Uncensored =     2,794
Limits: Lower =      2                       Left-censored =     1,206
        Upper = +inf                        Right-censored =         0

                                             LR chi2(3)       =  4712.61
                                             Prob > chi2      =   0.0000
Log likelihood = -2015.1258                  Pseudo R2        =   0.5390
```

gpa2	Coefficient	Std. err.	t	P>|t|	[95% conf. interval]	
hsgpa	.6586311	.0128699	51.18	0.000	.633399	.6838632
pincome	.3159297	.0074568	42.37	0.000	.3013103	.3305491
program	.5554416	.0147468	37.67	0.000	.5265297	.5843535
_cons	-.8902578	.0478484	-18.61	0.000	-.9840673	-.7964482
var(e.gpa2)	.161703	.0044004			.1533019	.1705645

tobit reports the coefficients for the latent regression model. Thus, we can interpret the coefficients just as we would the coefficients from OLS. For example, participation in a study-skills program increases the expected uncensored GPA by 0.56 points.

◁

▷ Example 2: Tobit model for a corner solution

Suppose that we are interested in the number of hours married women spend working for wages, and we treat observations recording zero hours as observed, per the corner-solution approach discussed Wooldridge (2010, chap. 16). We use the labor supply data extracted by Mroz (1987) from the 1975 PSID for 753 married women. The variable whrs75 records the annual number of hours worked. Forty-three percent of the surveyed women worked zero hours, and the remaining women worked on average 1,303 hours a year.

We regress hours worked on household income excluding wife's income (nwinc), years of schooling (wedyrs), years of labor market experience (wexper) and its square, age (wifeage), an indicator for the presence of children under 6 years of age at home (kl6), and an indicator for the presence of children from 6 to 18 years old at home (k618).

```
. use https://www.stata-press.com/data/r19/mroz87
(1975 PSID data from Mroz, 1987)
. tobit whrs75 nwinc wedyrs wexper c.wexper#c.wexper wifeage kl6 k618, ll(0)
Refining starting values:
Grid node 0:  Log likelihood = -3961.1577
Fitting full model:
Iteration 0:  Log likelihood = -3961.1577
Iteration 1:  Log likelihood = -3836.8928
Iteration 2:  Log likelihood = -3819.2637
Iteration 3:  Log likelihood = -3819.0948
Iteration 4:  Log likelihood = -3819.0946
```

```
Tobit regression                                Number of obs   =       753
                                                    Uncensored  =       428
Limits: Lower =     0                           Left-censored   =       325
        Upper = +inf                            Right-censored  =         0
                                                LR chi2(7)      =    271.59
                                                Prob > chi2     =    0.0000
Log likelihood = -3819.0946                     Pseudo R2       =    0.0343
```

whrs75	Coefficient	Std. err.	t	P>|t|	[95% conf. interval]	
nwinc	-8.814227	4.459089	-1.98	0.048	-17.56808	-.0603708
wedyrs	80.64541	21.58318	3.74	0.000	38.27441	123.0164
wexper	131.564	17.27935	7.61	0.000	97.64211	165.486
c.wexper#						
c.wexper	-1.864153	.5376606	-3.47	0.001	-2.919661	-.8086455
wifeage	-54.40491	7.418483	-7.33	0.000	-68.9685	-39.84133
kl6	-894.0202	111.8777	-7.99	0.000	-1113.653	-674.3875
k618	-16.21805	38.6413	-0.42	0.675	-92.07668	59.64057
_cons	965.3068	446.4351	2.16	0.031	88.88827	1841.725
var(e.whrs75)	1258927	93304.48			1088458	1456093

Unlike in example 1, we are interested in the marginal effect of the covariates on the observed outcome. We can use `margins` to estimate, for example, the average marginal effect of years of education on the expected value of the actual hours worked.

```
. margins, dydx(wedyrs) predict(ystar(0,.))
```

Average marginal effects   Number of obs = 753
Model VCE: OIM

Expression: E(whrs75*|whrs75>0), predict(ystar(0,.))
dy/dx wrt: wedyrs

	dy/dx	Delta-method std. err.	z	P>|z|	[95% conf. interval]
wedyrs	47.47306	12.6214	3.76	0.000	22.73558	72.21054

The average marginal effect of years of education on the actual hours worked is 47.47. See [R] **tobit postestimation** for more examples using `margins`.

◁

James Tobin (1918–2002) was an American economist who after education and research at Harvard moved to Yale, where he was on the faculty from 1950 to 1988. He made many outstanding contributions to economics and was awarded the Nobel Prize in 1981 "for his analysis of financial markets and their relations to expenditure decisions, employment, production and prices". He trained in the US Navy with the writer, Herman Wouk, who later fashioned a character after Tobin in the novel *The Caine Mutiny* (1951): "A mandarin-like midshipman named Tobit, with a domed forehead, measured quiet speech, and a mind like a sponge, was ahead of the field by a spacious percentage."

Stored results

`tobit` stores the following in `e()`:

Scalars
e(N)	number of observations
e(N_unc)	number of uncensored observations
e(N_lc)	number of left-censored observations
e(N_rc)	number of right-censored observations
e(k)	number of parameters
e(k_eq)	number of equations in e(b)
e(k_aux)	number of auxiliary parameters
e(k_dv)	number of dependent variables
e(df_m)	model degrees of freedom
e(df_r)	residual degrees of freedom
e(r2_p)	pseudo-R^2
e(ll)	log likelihood
e(ll_0)	log likelihood, constant-only model
e(N_clust)	number of clusters
e(chi2)	χ^2
e(F)	F statistic
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)	tobit
e(cmdline)	command as typed
e(depvar)	name of dependent variable
e(llopt)	minimum of *depvar* or contents of ll()
e(ulopt)	maximum of *depvar* or contents of ul()
e(wtype)	weight type
e(wexp)	weight expression
e(covariates)	list of covariates
e(title)	title in estimation output
e(clustvar)	name of cluster variable
e(offset)	linear offset variable
e(chi2type)	type of model χ^2 test
e(vce)	*vcetype* specified in vce()
e(vcetype)	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(method)	estimation method: ml
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(ilog)	iteration log (up to 20 iterations)
e(gradient)	gradient vector
e(V)	variance–covariance matrix of the estimators
e(V_modelbased)	model-based variance

Functions
e(sample)	marks estimation sample

In addition to the above, the following is stored in r():

Matrices
r(table)	matrix containing the coefficients with their standard errors, test statistics, *p*-values, and confidence intervals

Note that results stored in r() are updated when the command is replayed and will be replaced when any r-class command is run after the estimation command.

Methods and formulas

See *Methods and formulas* in [R] **intreg**.

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 *Maximum likelihood estimators* and *Methods and formulas*.

tobit also supports estimation with survey data. For details on VCEs with survey data, see [SVY] **Variance estimation**.

References

Amemiya, T. 1973. Regression analysis when the dependent variable is truncated normal. *Econometrica* 41: 997–1016. https://doi.org/10.2307/1914031.

———. 1984. Tobit models: A survey. *Journal of Econometrics* 24: 3–61. https://doi.org/10.1016/0304-4076(84)90074-5.

Belotti, F., P. Deb, W. G. Manning, and E. C. Norton. 2015. twopm: Two-part models. *Stata Journal* 15: 3–20.

Bertanha, M., A. H. McCallum, A. Payne, and N. Seegert. 2022. Bunching estimation of elasticities using Stata. *Stata Journal* 22: 597–624.

Burke, W. J. 2009. Fitting and interpreting Cragg's tobit alternative using Stata. *Stata Journal* 9: 584–592.

Cameron, A. C., and P. K. Trivedi. 2022. *Microeconometrics Using Stata*. 2nd ed. College Station, TX: Stata Press.

Canette, I. 2016. Understanding truncation and censoring. *The Stata Blog: Not Elsewhere Classified*. https://blog.stata.com/2016/12/13/understanding-truncation-and-censoring/.

Chernozhukov, V., I. Fernández-Val, S. Han, and A. Kowalski. 2019. Censored quantile instrumental-variable estimation with Stata. *Stata Journal* 19: 768–781.

Cong, R. 2000. sg144: Marginal effects of the tobit model. *Stata Technical Bulletin* 56: 27–34. Reprinted in *Stata Technical Bulletin Reprints*, vol. 10, pp. 189–197. College Station, TX: Stata Press.

Deb, P., E. C. Norton, and W. G. Manning. 2017. *Health Econometrics Using Stata*. College Station, TX: Stata Press.

Drukker, D. M. 2002. Bootstrapping a conditional moments test for normality after tobit estimation. *Stata Journal* 2: 125–139.

Goldberger, A. S. 1983. "Abnormal selection bias". In *Studies in Econometrics, Time Series, and Multivariate Statistics*, edited by S. Karlin, T. Amemiya, and L. A. Goodman, 67–84. New York: Academic Press. https://doi.org/10.1016/B978-0-12-398750-1.50009-7.

Hurd, M. 1979. Estimation in truncated samples when there is heteroscedasticity. *Journal of Econometrics* 11: 247–258. https://doi.org/10.1016/0304-4076(79)90039-3.

Long, J. S. 1997. *Regression Models for Categorical and Limited Dependent Variables*. Thousand Oaks, CA: Sage.

Maddala, G. S., and K. Lahiri. 2006. *Introduction to Econometrics*. 4th ed. New York: Wiley.

McDonald, J. F., and R. A. Moffitt. 1980. The use of tobit analysis. *Review of Economics and Statistics* 62: 318–321. https://doi.org/10.2307/1924766.

Mroz, T. A. 1987. The sensitivity of an empirical model of married women's hours of work to economic and statistical assumptions. *Econometrica* 55: 765–799. https://doi.org/10.2307/1911029.

Sánchez-Peñalver, A. 2019. Estimation methods in the presence of corner solutions. *Stata Journal* 19: 87–111.

Shiller, R. J. 1999. The ET interview: Professor James Tobin. *Econometric Theory* 15: 867–900. https://doi.org/10.1017/S0266466699156056.

Stewart, M. B. 1983. On least squares estimation when the dependent variable is grouped. *Review of Economic Studies* 50: 737–753. https://doi.org/10.2307/2297773.

Tobin, J. 1958. Estimation of relationships for limited dependent variables. *Econometrica* 26: 24–36. https://doi.org/10.2307/1907382.

Wooldridge, J. M. 2010. *Econometric Analysis of Cross Section and Panel Data*. 2nd ed. Cambridge, MA: MIT Press.

———. 2020. *Introductory Econometrics: A Modern Approach*. 7th ed. Boston: Cengage.

Also see