# Title



**tobit postestimation** — Postestimation tools for tobit



## Description

The following postestimation commands are available after `tobit`:

| Command | Description |
|---|---|
| `contrast` | contrasts and ANOVA-style joint tests of estimates |
| `estat ic` | Akaike's and Schwarz's Bayesian information criteria (AIC and BIC) |
| `estat summarize` | summary statistics for the estimation sample |
| `estat vce` | variance–covariance matrix of the estimators (VCE) |
| `estat` (svy) | postestimation statistics for survey data |
| `estimates` | cataloging estimation results |
| `forecast`[1] | dynamic forecasts and simulations |
| `hausman` | Hausman's specification test |
| `lincom` | point estimates, standard errors, testing, and inference for linear combinations of coefficients |
| `linktest` | link test for model specification |
| `lrtest`[2] | likelihood-ratio test |
| `margins` | marginal means, predictive margins, marginal effects, and average marginal effects |
| `marginsplot` | graph the results from margins (profile plots, interaction plots, etc.) |
| `nlcom` | point estimates, standard errors, testing, and inference for nonlinear combinations of coefficients |
| `predict` | predictions, residuals, influence statistics, and other diagnostic measures |
| `predictnl` | point estimates, standard errors, testing, and inference for generalized predictions |
| `pwcompare` | pairwise comparisons of estimates |
| `suest` | seemingly unrelated estimation |
| `test` | Wald tests of simple and composite linear hypotheses |
| `testnl` | Wald tests of nonlinear hypotheses |

[1] `forecast` is not appropriate with `svy` estimation results.

[2] `lrtest` is not appropriate with `svy` estimation results.

# Syntax for predict

`predict` [*type*] *newvar* [*if*] [*in*] [, *statistic* `nooffset`]

`predict` [*type*] {*stub** | $newvar_{\text{reg}}$ $newvar_{\text{sigma}}$} [*if*] [*in*] , `scores`

| *statistic* | Description |
|---|---|
| Main | |
| `xb` | linear prediction; the default |
| `stdp` | standard error of the linear prediction |
| `stdf` | standard error of the forecast |
| `pr(`*a*`,`*b*`)` | $\Pr(a < y_j < b)$ |
| `e(`*a*`,`*b*`)` | $E(y_j \,\vert\, a < y_j < b)$ |
| `ystar(`*a*`,`*b*`)` | $E(y_j^*)$, $y_j^* = \max\{a, \min(y_j, b)\}$ |

These statistics are available both in and out of sample; type `predict ... if e(sample) ...` if wanted only for the estimation sample.

`stdf` is not allowed with `svy` estimation results.

where *a* and *b* may be numbers or variables; *a* missing ($a \geq .$) means $-\infty$, and *b* missing ($b \geq .$) means $+\infty$; see [U] **12.2.1 Missing values**.

# Menu for predict

Statistics > Postestimation > Predictions, residuals, etc.

# Options for predict

Main

`xb`, the default, calculates the linear prediction.

`stdp` calculates the standard error of the prediction, which can be thought of as the standard error of the predicted expected value or mean for the observation's covariate pattern. The standard error of the prediction is also referred to as the standard error of the fitted value.

`stdf` calculates the standard error of the forecast, which is the standard error of the point prediction for 1 observation. It is commonly referred to as the standard error of the future or forecast value. By construction, the standard errors produced by `stdf` are always larger than those produced by `stdp`; see *Methods and formulas* in [R] **regress postestimation**.

`pr(`*a*`,`*b*`)` calculates $\Pr(a < \mathbf{x}_j\mathbf{b} + u_j < b)$, the probability that $y_j|\mathbf{x}_j$ would be observed in the interval $(a, b)$.

*a* and *b* may be specified as numbers or variable names; *lb* and *ub* are variable names;
`pr(20,30)` calculates $\Pr(20 < \mathbf{x}_j\mathbf{b} + u_j < 30)$;
`pr(`*lb*`,`*ub*`)` calculates $\Pr(lb < \mathbf{x}_j\mathbf{b} + u_j < ub)$; and
`pr(20,`*ub*`)` calculates $\Pr(20 < \mathbf{x}_j\mathbf{b} + u_j < ub)$.

*a* missing ($a \geq .$) means $-\infty$; `pr(.,30)` calculates $\Pr(-\infty < \mathbf{x}_j\mathbf{b} + u_j < 30)$;
`pr(`*lb*`,30)` calculates $\Pr(-\infty < \mathbf{x}_j\mathbf{b} + u_j < 30)$ in observations for which $lb \geq .$
and calculates $\Pr(lb < \mathbf{x}_j\mathbf{b} + u_j < 30)$ elsewhere.

$b$ missing ($b \geq .$) means $+\infty$; `pr(20,.)` calculates $\Pr(+\infty > \mathbf{x}_j\mathbf{b} + u_j > 20)$; `pr(20,`*ub*`)` calculates $\Pr(+\infty > \mathbf{x}_j\mathbf{b} + u_j > 20)$ in observations for which $ub \geq .$ and calculates $\Pr(20 < \mathbf{x}_j\mathbf{b} + u_j < ub)$ elsewhere.

`e(`*a*`,`*b*`)` calculates $E(\mathbf{x}_j\mathbf{b} + u_j \mid a < \mathbf{x}_j\mathbf{b} + u_j < b)$, the expected value of $y_j|\mathbf{x}_j$ conditional on $y_j|\mathbf{x}_j$ being in the interval $(a, b)$, meaning that $y_j|\mathbf{x}_j$ is truncated. *a* and *b* are specified as they are for `pr()`.

`ystar(`*a*`,`*b*`)` calculates $E(y_j^*)$, where $y_j^* = a$ if $\mathbf{x}_j\mathbf{b} + u_j \leq a$, $y_j^* = b$ if $\mathbf{x}_j\mathbf{b} + u_j \geq b$, and $y_j^* = \mathbf{x}_j\mathbf{b} + u_j$ otherwise, meaning that $y_j^*$ is censored. *a* and *b* are specified as they are for `pr()`.

`nooffset` is relevant only if you specified `offset(`*varname*`)`. It modifies the calculations made by `predict` so that they ignore the offset variable; the linear prediction is treated as $\mathbf{x}_j\mathbf{b}$ rather than as $\mathbf{x}_j\mathbf{b} + \text{offset}_j$.

`scores` calculates equation-level score variables.

The first new variable will contain $\partial \ln L / \partial(\mathbf{x}_j\boldsymbol{\beta})$.

The second new variable will contain $\partial \ln L / \partial\sigma$.

## Remarks and examples

stata.com

Following Cong (2000), write the tobit model as

$$y_i^* = \begin{cases} y_i, & \text{if } a < y_i < b \\ a, & \text{if } y_i \leq a \\ b, & \text{if } y_i \geq b \end{cases}$$

$y_i$ is a latent variable; instead, we observe $y_i^*$, which is bounded between $a$ and $b$ if $y_i$ is outside those bounds.

There are four types of marginal effects that may be of interest in the tobit model, depending on the application:

1. The $\beta$ coefficients themselves measure how the unobserved variable $y_i$ changes with respect to changes in the regressors.
2. The marginal effects of the truncated expected value $E(y_i^*|a < y_i^* < b)$ measure the changes in $y_i$ with respect to changes in the regressors among the subpopulation for which $y_i$ is not at a boundary.
3. The marginal effects of the censored expected value $E(y_i^*)$ describe how the observed variable $y_i^*$ changes with respect to the regressors.
4. The marginal effects of $\Pr(\mathrm{a} < \mathrm{y}_\mathrm{i}^* < \mathrm{b})$ describe how the probability of being uncensored changes with respect to the regressors.

In the next example, we show how to obtain each of these.

## Example 1

In example 3 of [R] **tobit**, we fit a two-limit tobit model of `mpg` on `wgt`.

```
. use http://www.stata-press.com/data/r13/auto
(1978 Automobile Data)

. generate wgt = weight/1000

. tobit mpg wgt, ll(17) ul(24)

Tobit regression                                  Number of obs   =         74
                                                  LR chi2(1)      =      77.60
                                                  Prob > chi2     =     0.0000
Log likelihood = -104.25976                       Pseudo R2       =     0.2712

------------------------------------------------------------------------------
         mpg |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         wgt |  -5.764448   .7245417    -7.96   0.000    -7.208457   -4.320438
       _cons |   38.07469   2.255917    16.88   0.000     33.57865    42.57072
-------------+----------------------------------------------------------------
      /sigma |   2.886337   .3952143                      2.098676    3.673998
------------------------------------------------------------------------------
  Obs. summary:         18  left-censored observations at mpg<=17
                        33     uncensored observations
                        23 right-censored observations at mpg>=24
```

`tobit` reports the $\beta$ coefficients for the latent regression model. The marginal effect of $x_k$ on $y$ is simply the corresponding $\beta_k$, because $E(y|x)$ is linear in $x$. Thus a 1,000-pound increase in a car's weight (which is a 1-unit increase in `wgt`) would lower fuel economy by 5.8 mpg.

To estimate the means of the marginal effects on the expected value of the censored outcome, conditional on weight being each of three values (2,000; 3,000; and 4,000 pounds), we type

```
. margins, dydx(wgt) predict(ystar(17,24)) at(wgt=(2 3 4))

Conditional marginal effects                      Number of obs   =         74
Model VCE    : OIM

Expression   : E(mpg*|17<mpg<24), predict(ystar(17,24))
dy/dx w.r.t. : wgt

1._at        : wgt             =           2

2._at        : wgt             =           3

3._at        : wgt             =           4

------------------------------------------------------------------------------
             |            Delta-method
             |      dy/dx   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
wgt          |
         _at |
          1  |    -1.0861    .311273    -3.49   0.000    -1.696184   -.4760162
          2  |   -4.45315   .4772541    -9.33   0.000    -5.388551    -3.51775
          3  |  -1.412822   .3289702    -4.29   0.000    -2.057591    -.768052
------------------------------------------------------------------------------
```

The $E(y^*|x)$ is nonlinear in $x$, so the marginal effect for a continuous covariate is not the same as the change in $y^*$ induced by a one-unit change in $x$. Recall that the marginal effect at a point is the slope of the tangent line at that point. In our example, we estimate the mean of the marginal effects for different values of `wgt`. The estimated mean of the marginal effects is $-1.1$ mpg for a 2,000 pound car; $-4.5$ mpg for a 3,000 pound car; and $-1.4$ mpg for a 4,000 pound car.

To estimate the means of the marginal effects on the expected value of the truncated outcome at the same levels of `wgt`, we type

```
. margins, dydx(wgt) predict(e(17,24)) at(wgt=(2 3 4))
Conditional marginal effects                    Number of obs     =         74
Model VCE    : OIM

Expression   : E(mpg|17<mpg<24), predict(e(17,24))
dy/dx w.r.t. : wgt

1._at        : wgt             =           2

2._at        : wgt             =           3

3._at        : wgt             =           4

------------------------------------------------------------------------------
             |            Delta-method
             |      dy/dx   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
wgt          |
         _at |
          1  |  -1.166572   .0827549   -14.10   0.000    -1.328768   -1.004375
          2  |  -2.308842   .4273727    -5.40   0.000    -3.146477   -1.471207
          3  |  -1.288896   .0889259   -14.49   0.000    -1.463188   -1.114604
------------------------------------------------------------------------------
```

The mean of the marginal effects of a change in `wgt` on $y_i$ (which is bounded between 17 and 24) is about $-1.2$ mpg for a 2,000 pound car; $-2.3$ mpg for a 3,000 pound car; and $-1.3$ for a 4,000 pound car.

◁

## References


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.

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


## Also see


[R] **tobit** — Tobit regression

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