xttobit postestimation — Postestimation tools for xttobit

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Postestimation commands

The following postestimation commands are available after `xttobit`:

Command	Description
`contrast`	contrasts and ANOVA-style joint tests of parameters
`estat ic`	Akaike's, consistent Akaike's, corrected Akaike's, and Schwarz's Bayesian information criteria (AIC, CAIC, AICc, and BIC, respectively)
`estat summarize`	summary statistics for the estimation sample
`estat vce`	variance–covariance matrix of the estimators (VCE)
`estimates`	cataloging estimation results
`etable`	table of estimation results
`forecast`	dynamic forecasts and simulations
`hausman`	Hausman's specification test
`lincom`	point estimates, standard errors, testing, and inference for linear combinations of parameters
`lrtest`	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 parameters
`predict`	predictions and their SEs, etc.
`predictnl`	point estimates, standard errors, testing, and inference for generalized predictions
`pwcompare`	pairwise comparisons of parameters
`test`	Wald tests of simple and composite linear hypotheses
`testnl`	Wald tests of nonlinear hypotheses

predict

Description for predict

predict creates a new variable containing predictions such as linear predictions, standard errors, probabilities, and expected values.

Menu for predict

Statistics > Postestimation

Syntax for predict

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

statistic	Description
Main	
xb	linear prediction; the default
stdp	standard error of the linear prediction
stdf	standard error of the linear forecast
pr(*a*,*b*)	$\Pr(a < y < b)$, marginal with respect to the random effect
e(*a*,*b*)	$E(y \mid a < y < b)$, marginal with respect to the random effect
ystar(*a*,*b*)	$E(y^*)$, $y^* = \max\{a, \min(y, b)\}$, marginal with respect to the random effect

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

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**.

Options for predict

Main

xb, the default, calculates the linear prediction $\mathbf{x}_{it}\boldsymbol{\beta}$ using the estimated fixed effects (coefficients) in the model. This is equivalent to fixing all random effects in the model to their theoretical (prior) mean value of zero.

stdp calculates the standard error of the linear prediction. It 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 linear forecast. This 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**.

`pr(`*a*`,`*b*`)` calculates estimates of $\Pr(a < y < b \mid \mathbf{x} = \mathbf{x}_{it})$, which is the probability that y would be observed in the interval (a, b), given the current values of the predictors, $\mathbf{x}_{it}$. The predictions are calculated marginally with respect to the random effect. That is, the random effect is integrated out of the prediction function. In the discussion that follows, these two conditions are implied.

a and *b* may be specified as numbers or variable names; *lb* and *ub* are variable names;
`pr(20,30)` calculates $\Pr(20 < y < 30)$;
`pr(`*lb*`,`*ub*`)` calculates $\Pr(lb < y < ub)$; and
`pr(20,`*ub*`)` calculates $\Pr(20 < y < ub)$.

a missing ($a \geq .$) means $-\infty$; `pr(.,30)` calculates $\Pr(-\infty < y < 30)$;
`pr(`*lb*`,30)` calculates $\Pr(-\infty < y < 30)$ in observations for which $lb \geq .$
(and calculates $\Pr(lb < y < 30)$ elsewhere).

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

`e(`*a*`,`*b*`)` calculates estimates of $E(y \mid a < y < b, \mathbf{x} = \mathbf{x}_{it})$, which is the expected value of y conditional on y being in the interval (a, b), meaning that y is truncated. *a* and *b* are specified as they are for `pr()`. The predictions are calculated marginally with respect to the random effect. That is, the random effect is integrated out of the prediction function.

`ystar(`*a*`,`*b*`)` calculates estimates of $E(y^* \mid \mathbf{x} = \mathbf{x}_{it})$, where $y^* = a$ if $y \leq a$, $y^* = b$ if $y \geq b$, and $y^* = y$ otherwise, meaning that y^* is the censored version of y. *a* and *b* are specified as they are for `pr()`. The predictions are calculated marginally with respect to the random effect. That is, the random effect is integrated out of the prediction function.

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

margins

Description for margins

margins estimates margins of response for linear predictions, probabilities, and expected values.

Menu for margins

Statistics > Postestimation

Syntax for margins

margins [*marginlist*] [, *options*]

margins [*marginlist*] , predict(*statistic* ...) [predict(*statistic* ...) ...] [*options*]

statistic	Description
xb	linear prediction, the default
pr(*a*,*b*)	$\Pr(a < y < b)$, marginal with respect to the random effect
e(*a*,*b*)	$E(y \mid a < y < b)$, marginal with respect to the random effect
ystar(*a*,*b*)	$E(y^*)$, $y^* = \max\{a, \min(y, b)\}$, marginal with respect to the random effect
stdp	not allowed with margins
stdf	not allowed with margins

Statistics not allowed with margins are functions of stochastic quantities other than e(b).

For the full syntax, see [R] **margins**.

Remarks and examples

▷ Example 1: Average marginal probabilities at specified covariate values

In example 1 of [XT] **xttobit**, we fit a random-effects model of wages. Say that we want to know how union membership status affects the probability that a worker's wage will be "low", where low means a log wage that is less than the 20th percentile of all observations in our dataset. First, we use centile to find the 20th percentile of ln_wage:

```
. use https://www.stata-press.com/data/r19/nlswork3
(National Longitudinal Survey of Young Women, 14-24 years old in 1968)
. xttobit ln_wage i.union age grade not_smsa south##c.year, ul(1.9)
  (output omitted)
. centile ln_wage, centile(20)

                                                      Binom. interp.
    Variable |       Obs  Percentile    Centile      [95% conf. interval]
-------------+-------------------------------------------------------------
     ln_wage |    28,534          20   1.301507      1.297063    1.308635
```

Now, we use `margins` to obtain the effect of union status on the probability that the log of wages is in the bottom 20% of women. Given the results from `centile`, that corresponds to the log of wages being below 1.30. We evaluate the effect for two groups: 1) women age 30 living in the south in 1988 who graduated from high school but had no more schooling and 2) the same group of women who instead graduated from college (`grade=16`).

```
. margins, dydx(union) predict(pr(.,1.30))
> at(age=30 south=1 year=88 grade=12 union=0)
> at(age=30 south=1 year=88 grade=16 union=0)

Average marginal effects                              Number of obs = 19,224
Model VCE: OIM

Expression: Pr(ln_wage<1.30), predict(pr(.,1.30))
dy/dx wrt:  1.union
1._at: union =  0
       age   = 30
       grade = 12
       south =  1
       year  = 88
2._at: union =  0
       age   = 30
       grade = 16
       south =  1
       year  = 88

------------------------------------------------------------------------------
             |            Delta-method
             |      dy/dx   std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
0.union      |  (base outcome)
-------------+----------------------------------------------------------------
1.union      |
         _at |
          1  |  -.0992088   .0057424   -17.28   0.000    -.1104637   -.0879539
          2  |  -.0374347   .0033407   -11.21   0.000    -.0439823   -.0308871
------------------------------------------------------------------------------
Note: dy/dx for factor levels is the discrete change from the base level.
```

For the first group of women, according to our fitted model, being in a union lowers the probability of being classified as a low-wage worker by almost 10 percentage points. Being a college graduate attenuates this effect to just above 3.7 percentage points.

◁

Methods and formulas

The following uses the notation introduced in *Remarks and examples* of [XT] **xttobit**.

The marginal probability that y_{it} is observed in the interval $(\ell\ell_{it}, u\ell_{it})$, obtained by specifying the `pr(`a`,`b`)` option, is calculated as

$$\begin{aligned} \text{pr}(\ell\ell_{it}, u\ell_{it}) &= \Pr(\ell\ell_{it} < \mathbf{x}_{it}\boldsymbol{\beta} + \nu_i + \epsilon_{it} < u\ell_{it}) \\ &= \Phi\left(\frac{u\ell_{it} - \mathbf{x}_{it}\widehat{\boldsymbol{\beta}}}{\widehat{\sigma}}\right) - \Phi\left(\frac{\ell\ell_{it} - \mathbf{x}_{it}\widehat{\boldsymbol{\beta}}}{\widehat{\sigma}}\right) \end{aligned} \tag{1}$$

where $\widehat{\sigma}$ is the square root of the estimated marginal variance of the linear predictor, $\sqrt{\widehat{\sigma}_\epsilon^2 + \widehat{\sigma}_\nu^2}$.

The `e(a,b)` option computes the expected value of y_{it} conditional on y_{it} being in the interval $(\ell\ell_{it}, u\ell_{it})$, that is, when y_{it} is truncated. The expected value is calculated as

$$\begin{aligned} e(\ell\ell_{it}, u\ell_{it}) &= E(\mathbf{x}_{it}\boldsymbol{\beta} + \nu_i + \epsilon_{it} \mid \ell\ell_{it} < \mathbf{x}_{it}\boldsymbol{\beta} + \nu_i + \epsilon_{it} < u\ell_{it}) \\ &= \mathbf{x}_{it}\widehat{\boldsymbol{\beta}} - \widehat{\sigma}\frac{\phi\left(\frac{u\ell_{it}-\mathbf{x}_{it}\widehat{\boldsymbol{\beta}}}{\widehat{\sigma}}\right) - \phi\left(\frac{\ell\ell_{it}-\mathbf{x}_{it}\widehat{\boldsymbol{\beta}}}{\widehat{\sigma}}\right)}{\Phi\left(\frac{u\ell_{it}-\mathbf{x}_{it}\widehat{\boldsymbol{\beta}}}{\widehat{\sigma}}\right) - \Phi\left(\frac{\ell\ell_{it}-\mathbf{x}_{it}\widehat{\boldsymbol{\beta}}}{\widehat{\sigma}}\right)} \end{aligned} \tag{2}$$

where ϕ is the normal density and Φ is the cumulative normal distribution.

You can also compute the expected value of y_{it}, where y_{it} is assumed censored at $\ell\ell_{it}$ and $u\ell_{it}$ by specifying the option `ystar(a,b)`. This expected value is

$$y^*_{it} = \begin{cases} \ell\ell_{it} & \text{if } y_{it} \le \ell\ell_{it} \\ \mathbf{x}_{it}\boldsymbol{\beta} + \epsilon_{it} & \text{if } \ell\ell_{it} < y_{it} < u\ell_{it} \\ u\ell_{it} & \text{if } y_{it} \ge u\ell_{it} \end{cases}$$

This computation can be expressed in several ways, but the most intuitive formulation involves a combination of (1) and (2):

$$E(y^*_{it}) = \text{pr}(-\infty, \ell\ell_{it})\ell\ell_{it} + \text{pr}(\ell\ell_{it}, u\ell_{it})e(\ell\ell_{it}, u\ell_{it}) + \text{pr}(u\ell_{it}, +\infty)u\ell_{it}$$

Also see

[XT] **xttobit** — Random-effects tobit model

[U] 20 Estimation and postestimation commands

For suggested citations, see the FAQ on citing Stata documentation.