Title

heckoprobit postestimation — Postestimation tools for heckoprobit

Description
Syntax for predict
Menu for predict
Options for predict
Remarks and examples
Methods and formulas
Also see

Description

The following postestimation commands are available after `heckoprobit`:

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
`lincom`	point estimates, standard errors, testing, and inference for linear combinations of coefficients
`lrtest`[1]	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, standard errors, 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] `lrtest` is not appropriate with `svy` estimation results.

Syntax for predict

predict [*type*] { *stub** | *newvar* | *newvarlist* } [*if*] [*in*] [, *statistic*
  outcome(*outcome*) nooffset]

predict [*type*] { *stub** | $newvar_{reg}$ $newvar_{sel}$ $newvar_1$ ... $newvar_h$ $newvar_{athrho}$ }
  [*if*] [*in*] , scores

statistic	Description
Main	
pmargin	marginal probabilities; the default
p1	bivariate probabilities of levels with selection
p0	bivariate probabilities of levels with no selection
pcond1	probabilities of levels conditional on selection
pcond0	probabilities of levels conditional on no selection
psel	selection probability
xb	linear prediction
stdp	standard error of the linear prediction
xbsel	linear prediction for selection equation
stdpsel	standard error of the linear prediction for selection equation

If you do not specify outcome(), pmargin (with one new variable specified) assumes outcome(#1).

You specify one or k new variables with pmargin, where k is the number of outcomes.

You specify one new variable with psel, xb, stdp, xbsel, and stdpsel.

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

Menu for predict

Statistics > Postestimation > Predictions, residuals, etc.

Options for predict

Main

pmargin, the default, calculates the predicted marginal probabilities.

You specify one or k new variables, where k is the number of categories of the outcome variable y_j. If you specify the outcome() option, you must specify one new variable. If you specify one new variable and do not specify outcome(), outcome(#1) is assumed.

When outcome() is specified, the marginal probability that y_j is equal to the level outcome() is calculated. When outcome() is not specified, the marginal probabilities for each outcome level are calculated.

p1 calculates the predicted bivariate probabilities of outcome levels with selection.

You specify one or k new variables, where k is the number of categories of the outcome variable y_j. If you specify the outcome() option, you must specify one new variable. If you specify one new variable and do not specify outcome(), outcome(#1) is assumed.

When outcome() is specified, the bivariate probability that y_j is equal to the level outcome() and that y_j is observed is calculated. When outcome() is not specified, the bivariate probabilities for each outcome level and selection are calculated.

p0 calculates the predicted bivariate probabilities of outcome levels with no selection.

You specify one or k new variables, where k is the number of categories of the outcome variable y_j. If you specify the outcome() option, you must specify one new variable. If you specify one new variable and do not specify outcome(), outcome(#1) is assumed.

When outcome() is specified, the bivariate probability that y_j is equal to the level outcome() and that y_j is not observed is calculated. When outcome() is not specified, the bivariate probabilities for each outcome level and no selection are calculated.

pcond1 calculates the predicted probabilities of outcome levels conditional on selection.

You specify one or k new variables, where k is the number of categories of the outcome variable y_j. If you specify the outcome() option, you must specify one new variable. If you specify one new variable and do not specify outcome(), outcome(#1) is assumed.

When outcome() is specified, the probability that y_j is equal to the level outcome() given that y_j is observed is calculated. When outcome() is not specified, the probabilities for each outcome level conditional on selection are calculated.

pcond0 calculates the predicted probabilities of outcome levels conditional on no selection.

You specify one or k new variables, where k is the number of categories of the outcome variable y_j. If you specify the outcome() option, you must specify one new variable. If you specify one new variable and do not specify outcome(), outcome(#1) is assumed.

When outcome() is specified, the probability that y_j is equal to the level outcome() given that y_j is not observed is calculated. When outcome() is not specified, the probabilities for each outcome level conditional on no selection are calculated.

psel calculates the predicted univariate (marginal) probability of selection.

xb calculates the linear prediction for outcome variable, which is $\mathbf{x}_j\boldsymbol{\beta}$ if offset() was not specified and $\mathbf{x}_j\boldsymbol{\beta} + \text{offset}_j^{\beta}$ if offset() was specified.

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.

xbsel calculates the linear prediction for the selection equation, which is $\mathbf{z}_j\boldsymbol{\gamma}$ if offset() was not specified in select() and $\mathbf{z}_j\boldsymbol{\gamma} + \text{offset}_j^{\gamma}$ if offset() was specified in select().

stdpsel calculates the standard error of the linear prediction for the selection equation.

outcome(*outcome*) specifies for which outcome the predicted probabilities are to be calculated. outcome() should contain either one value of the dependent variable or one of #1, #2, ..., with #1 meaning the first category of the dependent variable, #2 meaning the second category, etc.

nooffset is relevant only if you specified offset(*varname*) for heckoprobit. 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 $\partial \ln L/\partial(\mathbf{z}_j\boldsymbol{\gamma})$.

When the dependent variable takes k different values, new variables three through $k+1$ will contain $\partial \ln L/\partial(\kappa_{j-2})$.

The last new variable will contain $\partial \ln L/\partial(\operatorname{atanh}\rho)$.

Remarks and examples

stata.com

▷ Example 1

In example 1 of [R] **heckoprobit**, we examined a simulated dataset of 5,000 women, 3,480 of whom work and can thus report job satisfaction. Using job satisfaction (`satisfaction`) as the outcome variable and employment (`work`) as the selection variable, we estimated the parameters of an ordered probit sample-selection model. Covariates age (`age`), years of education (`education`), number of children (`children`), and marital status (`married`) are expected to affect selection. The outcome, job satisfaction, is affected by age (`age`) and education (`education`).

We first reestimate the parameters of the regression, but this time we request a robust variance estimator:

```
. use http://www.stata-press.com/data/r13/womensat
(Job satisfaction, female)
. heckoprobit satisfaction education age,
> select(work=education age i.married##c.children) vce(robust)
  (output omitted )
```

We then use `margins` (see [R] **margins**) to estimate the average marginal effect of education on the probability of having low job satisfaction.

```
. margins, dydx(education) vce(unconditional)
Average marginal effects                          Number of obs   =       5000
Expression   : Pr(satisfaction=1), predict()
dy/dx w.r.t. : education
```

	dy/dx	Unconditional Std. Err.	z	P>|z|	[95% Conf.	Interval]
education	-.0234776	.0019176	-12.24	0.000	-.027236	-.0197192

The estimated average marginal effect of education on the probability of having low job satisfaction is approximately −0.023.

◁

Methods and formulas

The ordinal outcome equation is

$$y_j = \sum_{h=1}^{H} v_h 1\left(\kappa_{h-1} < \mathbf{x}_j\boldsymbol{\beta} + u_{1j} \leq \kappa_h\right)$$

where $\mathbf{x}_j$ is the outcome covariates, $\boldsymbol{\beta}$ is the coefficients, and u_{1j} is a random-error term. The observed outcome values $v_1, \ldots, v_H$ are integers such that $v_i < v_m$ for $i < m$. $\kappa_1, \ldots, \kappa_{H-1}$ are real numbers such that $\kappa_i < \kappa_m$ for $i < m$. κ_0 is taken as $-\infty$ and κ_H is taken as $+\infty$.

The selection equation is

$$s_j = 1(\mathbf{z}_j\boldsymbol{\gamma} + u_{2j} > 0)$$

where $s_j = 1$ if we observed y_j and 0 otherwise, $\mathbf{z}_j$ is the covariates used to model the selection process, $\boldsymbol{\gamma}$ is the coefficients for the selection process, and u_{2j} is a random-error term.

(u_{1j}, u_{2j}) have bivariate normal distribution with mean zero and variance matrix

$$\begin{bmatrix} 1 & \rho \\ \rho & 1 \end{bmatrix}$$

The probability of selection is

$$\Pr(s_j = 1) = \Phi(\mathbf{z}_j\boldsymbol{\gamma} + \text{offset}_j^{\gamma})$$

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

The probability of selection and the outcome $y_j = v_h$ is

$$\begin{aligned}\Pr(y_j = v_h, s_j = 1) = \Phi_2\left(\mathbf{z}_j\boldsymbol{\gamma} + \text{offset}_j^{\gamma}, \kappa_h - x_j\boldsymbol{\beta} - \text{offset}_j^{\beta}, -\rho\right) \\ - \Phi_2\left(\mathbf{z}_j\boldsymbol{\gamma} + \text{offset}_j^{\gamma}, \kappa_{h-1} - \mathbf{x}_j\boldsymbol{\beta} - \text{offset}_j^{\beta}, -\rho\right)\end{aligned}$$

$\Phi_2(\cdot)$ is the cumulative bivariate normal distribution function (with mean $[\,0 \;\; 0\,]'$).

The probability of y_j not being selected and the outcome $y_j = v_h$ is

$$\begin{aligned}\Pr(y_j = v_h, s_j = 0) = \Phi_2\left(-\mathbf{z}_j\boldsymbol{\gamma} - \text{offset}_j^{\gamma}, \kappa_h - x_j\boldsymbol{\beta} - \text{offset}_j^{\beta}, \rho\right) \\ - \Phi_2\left(-\mathbf{z}_j\boldsymbol{\gamma} - \text{offset}_j^{\gamma}, \kappa_{h-1} - \mathbf{x}_j\boldsymbol{\beta} - \text{offset}_j^{\beta}, \rho\right)\end{aligned}$$

The probability of outcome $y_j = v_h$ given selection is

$$\Pr(y_j = v_h | s_j = 1) = \frac{\Pr(y_j = v_h, s_j = 1)}{\Pr(s_j = 1)}$$

The probability of outcome $y_j = v_h$ given y_j is not selected is

$$\Pr(y_j = v_h | s_j = 0) = \frac{\Pr(y_j = v_h, s_j = 0)}{\Pr(s_j = 0)}$$

The marginal probabilities of the outcome y_j are

$$\begin{aligned}\Pr(y_j = v_1) &= \Phi(\kappa_1 - x_j\boldsymbol{\beta} - \text{offset}_j^{\beta}) \\ \Pr(y_j = v_H) &= 1 - \Phi(\kappa_{H-1} - x_j\boldsymbol{\beta} - \text{offset}_j^{\beta}) \\ \Pr(y_j = v_h) &= \Phi(\kappa_h - x_j\boldsymbol{\beta} - \text{offset}_j^{\beta}) - \Phi(\kappa_{h-1} - x_j\boldsymbol{\beta} - \text{offset}_j^{\beta})\end{aligned}$$

Also see

[R] **heckoprobit** — Ordered probit model with sample selection

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