Postestimation commands predict margins Remarks and examples
Methods and formulas Also see

Postestimation commands

The following postestimation commands are available after `heckpoisson`:

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)
`estat` (svy)	postestimation statistics for survey data
`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`	number of events, incidence rates, probabilities, etc.
`predictnl`	point estimates, standard errors, testing, and inference for generalized predictions
`pwcompare`	pairwise comparisons of parameters
`suest`	seemingly unrelated estimation
`test`	Wald tests of simple and composite linear hypotheses
`testnl`	Wald tests of nonlinear hypotheses

*`forecast`, `hausman`, and `lrtest` are not appropriate with `svy` estimation results.

predict

Description for predict

predict creates new variables containing predictions such as number of events, incidence rates, conditional predicted number of events, probabilities, linear predictions, and equation-level scores.

Menu for predict

Statistics > Postestimation

Syntax for predict

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

predict [*type*] *stub** [*if*] [*in*], scores

statistic	Description
Main	
n	number of events; the default
ir	incidence rate
ncond	predicted number of events conditional on y_j being observed
pr(*n*)	$\Pr(y_j = n)$
pr(*a*,*b*)	$\Pr(a \leq y_j \leq b)$
psel	$\Pr(y_j \text{ observed})$
xb	linear prediction
xbsel	linear prediction for selection equation

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

Options for predict

Main

n, the default, calculates the predicted number of events, which is $\exp(\mathbf{x}_j\beta + \sigma^2/2)$ if neither offset() nor exposure() was specified when the model was fit; is $\exp(\mathbf{x}_j\beta + \sigma^2/2 + \text{offset}_j)$ if offset() was specified; or is $\exp(\mathbf{x}_j\beta + \sigma^2/2) \times \text{exposure}_i$ if exposure() was specified.

ir calculates the incidence rate $\exp(\mathbf{x}_j\beta + \sigma^2/2)$, which is the predicted number of events when exposure is 1. Specifying ir is equivalent to specifying n when neither offset() nor exposure() was specified when the model was fit.

ncond calculates the predicted number of events conditional on y_j being observed, which is $\exp(\mathbf{x}_j\boldsymbol{\beta} + \sigma^2/2)\Phi(\mathbf{w}_j\gamma + \rho\sigma)/\Phi(\mathbf{w}_j\gamma)$.

pr(*n*) calculates the probability $\Pr(y_j = n)$, where n is a nonnegative integer that may be specified as a number or a variable.

`pr(`a`,`b`)` calculates the probability $\Pr(a \leq y_j \leq b)$, where a and b are nonnegative integers that may be specified as numbers or variables;

b missing ($b \geq .$) means $+\infty$;
`pr(20,.)` calculates $\Pr(y_j \geq 20)$;
`pr(20,`b`)` calculates $\Pr(y_j \geq 20)$ in observations for which $b \geq .$ and calculates $\Pr(20 \leq y_j \leq b)$ elsewhere.

`pr(.,`b`)` produces a syntax error. A missing value in an observation of the variable a causes a missing value in that observation for `pr(`a`,`b`)`.

`psel` calculates the probability of selection (or being observed):
$\Pr(y_j \text{ observed}) = \Pr(\mathbf{w}_j\gamma + \epsilon_{2j} > 0)$

`xb` calculates the linear prediction for the dependent count variable, which is $\mathbf{x}_j\boldsymbol{\beta}$ if neither `offset()` nor `exposure()` was specified; $\mathbf{x}_j\boldsymbol{\beta} + \text{offset}_j^{\beta}$ if `offset()` was specified; or $\mathbf{x}_j\boldsymbol{\beta} + \ln(\text{exposure}_j)$ if `exposure()` was specified.

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

`nooffset` is relevant only if you specified `offset()` or `exposure()` when you fit the model. It modifies the calculations made by `predict` so that they ignore the offset or exposure variable; the linear prediction is treated as $\mathbf{x}_j\boldsymbol{\beta}$ rather than as $\mathbf{x}_j\boldsymbol{\beta} + \text{offset}_j$ or $\mathbf{x}_j\boldsymbol{\beta} + \ln(\text{exposure}_j)$.

`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 $\partial \ln L/\partial(\mathbf{w}_j\boldsymbol{\gamma})$.

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

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

margins

Description for margins

margins estimates margins of response for number of events, incidence rates, conditional predicted number of events, probabilities, and linear predictions.

Menu for margins

Statistics > Postestimation

Syntax for margins

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

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

statistic	Description
n	number of events; the default
ir	incidence rate
ncond	predicted number of events conditional on y_j being observed
pr(*n*)	$\Pr(y_j = n)$
pr(*a*,*b*)	$\Pr(a \leq y_j \leq b)$
psel	$\Pr(y_j \text{ observed})$
xb	linear prediction
xbsel	linear prediction for selection equation

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: Obtaining margins for a count model with selection

In example 1 of [R] **heckpoisson**, we fit a model for the number of patents. In that example, we are interested in the effect of R&D expenditures on the number of patents received by a firm. We continue that example to determine the magnitude of the effect of R&D expenditures on the number of patents and compare this effect for IT and non-IT sectors.

After reading in the data and fitting the model, we use margins to estimate the effect of an increase of a million dollars in R&D expenditures (expenditure) on the number of patents (npatents) for firms in the IT and non-IT sectors (tech).

To do this, we use the at() option of margins. We use the observed values in our first scenario, so we tell margins to set expenditure equal to itself. For our second scenario, we tell margins to set expenditure equal to the observed value plus 1 because expenditures are measured in millions of dollars. We include the post option so that we can perform additional calculations later.

```
. use https://www.stata-press.com/data/r19/patent
(Fictional data on patents and R&D)

. quietly heckpoisson npatents expenditure i.tech,
> select(applied = expenditure size i.tech)

. margins i.tech, at(expenditure = generate(expenditure))
> at(expenditure = generate(expenditure+1)) post

Predictive margins                                 Number of obs = 10,000
Model VCE: OIM

Expression: Predicted number of events, predict()
1._at: expenditure =   expenditure
2._at: expenditure = expenditure+1
```

	Margin	Delta-method std. err.	z	P>|z|	[95% conf. interval]	
_at#tech						
1 #						
Non-IT se..	1.276213	.0556644	22.93	0.000	1.167112	1.385313
1#IT sector	2.287013	.080119	28.55	0.000	2.129983	2.444044
2 #						
Non-IT se..	2.099539	.131364	15.98	0.000	1.84207	2.357007
2#IT sector	3.76244	.2226221	16.90	0.000	3.326109	4.198771

The output indicates that the expected number of patents for non-IT firms is about 1.28 compared with 2.29 for firms in the IT sector.

The second scenario shows the expected number of patents after our hypothetical increase in R&D expenditures. In the non-IT sector, the expected number of patents received would be about 2.10 compared with 3.76 in the IT sector. It appears that increasing expenditures may have a larger effect for IT firms—the difference between the two scenarios is 1.47 for IT firms and only 0.82 for non-IT firms. We can test whether the effect of increasing expenditures is different for IT and non-IT firms. We use `lincom` to obtain an estimate of the difference in the differences between scenarios for the two sectors and a test of its significance. We ask for the differences by referring to the scenarios as `1._at` and `2._at` and by referring to the sector using the value that corresponds to the IT sector indicator, `1.tech` for IT firms and `0.tech` otherwise.

```
. lincom (_b[2._at#1.tech] - _b[1._at#1.tech]) -
> (_b[2._at#0.tech] - _b[1._at#0.tech])

 ( 1)  1bn._at#0bn.tech - 1bn._at#1.tech - 2._at#0bn.tech + 2._at#1.tech = 0
```

	Coefficient	Std. err.	z	P>|z|	[95% conf. interval]	
(1)	.6521006	.0917299	7.11	0.000	.4723134	.8318878

We find that the expected effect of increasing R&D expenditures by one million dollars is 0.65 patents larger for IT firms than for non-IT firms, and this difference is significantly different from 0.

◁

Methods and formulas

Suppose that the count outcome y_j has covariates $\mathbf{x}_j$ and the selection outcome s_j has covariates $\mathbf{w}_j$. y_j is assumed to have a Poisson distribution, conditional on $\mathbf{x}_j$, with conditional mean

$$E(y_j|\mathbf{x}_j, \epsilon_{1j}) = \mu_j = \exp(\mathbf{x}_j\boldsymbol{\beta} + \epsilon_{1j})$$

s_j is a binary outcome from a latent-variable model:

$$s_j = \begin{cases} 1, & \text{if } \mathbf{w}_i\gamma + \epsilon_{2j} > 0 \\ 0, & \text{otherwise} \end{cases}$$

The expectation of y_j conditional on covariates $\mathbf{x}_j$ for the whole population is

$$E(y_j|\mathbf{x}_j) = \exp(\mathbf{x}_j\boldsymbol{\beta} + \sigma^2/2)$$

Furthermore, if we want the expectation of y_j only if it was observed, then the formula is

$$E(y_j|\mathbf{x}_j, \mathbf{w}_j, s_j = 1) = \exp(\mathbf{x}_j\boldsymbol{\beta} + \sigma^2/2)\frac{\Phi(\mathbf{w}_j\gamma + \rho\sigma)}{\Phi(\mathbf{w}_j\gamma)}$$

We note that if $\rho = 0$, this expectation is the same as its population version.

We can also predict the probability of y_j conditional on $\mathbf{x}_j$. Note that although y_j is Poisson-distributed conditional on ϵ_1 and $\mathbf{x}_j$, the distribution of y_j is unknown unconditional on ϵ_1.

$$\Pr(y_j = n|\mathbf{x}_j) = \int_{-\infty}^{\infty} \Pr(y_j = n|\mathbf{x}_j, \epsilon_1)\phi(\epsilon_1/\sigma)d\epsilon_1$$

As in the implementation of log likelihood, we approximate this integral by Gauss–Hermite quadrature.

Also see

[R] **heckpoisson** — Poisson regression with sample selection

[U] 20 Estimation and postestimation commands