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**ziologit postestimation** — Postestimation tools for ziologit

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# **Postestimation commands**

The following postestimation commands are available after ziologit:

Command	Description					
contrast	contrasts and ANOVA-style joint tests of estimates					
estat ic	Akaike's, consistent Akaike's, corrected Akaike's, and Schwarz's Bayesian information criteria (AIC, CAIC, AICc, 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					
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 coefficients					
*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 coefficients					
predict	probabilities, linear predictions and their SEs, etc.					
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					

<sup>\*</sup>forecast, hausman, and lrtest are not appropriate with svy estimation results.

## predict

#### **Description for predict**

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

#### Menu for predict

Statistics > Postestimation

#### Syntax for predict

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

statistic	Description			
Main				
pmargin	marginal probabilities of levels, $Pr(y_j = h)$ ; the default			
pjoint1	joint probabilities of levels and susceptibility, $Pr(y_j = h, s_j = 1)$			
pcond1	probabilities of levels conditional on susceptibility, $Pr(y_j = h   s_j = 1)$			
ps	probability of susceptibility, $Pr(s_j = 1)$			
pns	probability of nonsusceptibility, $Pr(s_j = 0)$			
xb	linear prediction			
xbinfl	linear prediction for inflation equation			
stdp	standard error of the linear prediction			
stdpinfl	standard error of the linear prediction for inflation equation			

If you do not specify outcome(), pmargin, pjoint1, and pcond1 (with one new variable specified) assume outcome(#1).

You specify one or k new variables with pmargin, pjoint1, and pcond1, where k is the number of outcomes.

You specify one new variable with ps, pns, xb, xbinfl, stdp, and stdpinfl.

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

pmargin, the default, calculates the predicted marginal probabilities of outcome levels,  $Pr(y_i = h)$ . pjoint1 calculates the predicted joint probabilities of outcome levels and susceptibility,  $Pr(y_i =$  $h, s_i = 1$ ).

pcond1 calculates the predicted probabilities of outcome levels conditional on susceptibility,  $Pr(y_j =$  $h|s_i = 1$ ).

With pmargin, pjoint1, and pcond1, you can compute predicted probabilities for one or for all outcome levels. When you specify one new variable, predict computes probabilities for the first outcome level. You can specify the outcome (#i) option to obtain probabilities for the ith level. When you specify multiple new variables or a stub, predict computes probabilities for all outcome levels. The behavior of predict with one new variable is equivalent to specifying outcome(#1).

ps and pns calculate the predicted marginal probability of susceptibility  $[Pr(s_i = 1)]$  and of nonsusceptibility  $[Pr(s_i = 0)]$ , respectively.

In econometrics literature, probabilities of susceptibility and nonsusceptibility are known as probabilities of participation and nonparticipation. Similarly to predict after zioprobit, you can use options ppar and pppar to compute these probabilities. Options ppar and pppar produce identical results to the respective options ps and pns but label new variables as Pr(participation) and Pr(nonparticipation) instead of Pr(susceptible) and Pr(nonsusceptible).

xb calculates the linear prediction for the ordered logit equation, which is  $x_i\beta$  if offset() was not specified with ziologit and is  $x_i\beta$  + offset; if offset() was specified.

xbinfl calculates the linear prediction for the inflation equation, which is  $\mathbf{z}_i \gamma$  if offset() was not specified in inflate() and is  $\mathbf{z}_{i}\gamma$  + offset; if offset() was specified in inflate().

stdp calculates the standard error of the linear prediction for the ordered logit equation.

stdpinf1 calculates the standard error of the linear prediction for the inflation equation.

outcome (outcome) specifies the outcome for which 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. outcome() is allowed only with pmargin, pjoint1, and pcond1.

nooffset is relevant only if you specified offset (varname) with ziologit or within the inflate() option. It modifies the calculations made by predict so that they ignore the offset variable; that is, the linear prediction for the main regression equation is treated as  $\mathbf{x}_{i}\boldsymbol{\beta}$  rather than as  $\mathbf{x}_{i}\boldsymbol{\beta}$  + offset<sub>i</sub><sup> $\beta$ </sup> and the linear prediction for the inflation equation is treated as  $\mathbf{z}_i \gamma$  rather than as  $\mathbf{z}_i \gamma + \text{offset}_i^{\bar{\gamma}}$ . scores calculates equation-level score variables.

The first new variable will contain  $\partial \ln L/\partial(\mathbf{x}_i\beta)$ . In the absence of independent variables in the main equation, this variable is not stored.

The second new variable will contain  $\partial \ln L/\partial(\mathbf{z}_i \boldsymbol{\gamma})$ .

When the dependent variable takes k different values, the third new variable through new variable k+1 will contain  $\partial \ln L/\partial(\kappa_h)$  for  $h=0,1,\ldots,k-2$ .

# margins

## **Description for margins**

margins estimates margins of response for probabilities and linear predictions.

### Menu for margins

Statistics > Postestimation

## Syntax for margins

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

statistic	Description
default	marginal probabilities for each outcome
pmargin	marginal probabilities of levels, $Pr(y_j = h)$ ; the default
 pjoint1	joint probabilities of levels and susceptibility, $Pr(y_j = h, s_j = 1)$
pcond1	probabilities of levels conditional on susceptibility, $Pr(y_j = h   s_j = 1)$
ps	probability of susceptibility, $Pr(s_j = 1)$
pns	probability of nonsusceptibility, $Pr(s_j = 0)$
xb	linear prediction
xbinfl	linear prediction for inflation equation
stdp	not allowed with margins
stdpinfl	not allowed with margins

pmargin, pjoint1, and pcond1 default to the first outcome.

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

For the full syntax, see [R] margins.

# Remarks and examples

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The ZIOL model allows all the predictions and marginal effects available with the standard ologit model (see [R] ologit postestimation), along with additional predictions and marginal effects related to the inflation equation for susceptibility. The probabilities of susceptibility and nonsusceptibility can be calculated using options ps and pns, respectively. If you prefer an alternative terminology of probabilities of participation and nonparticipation, you can instead use options ppar and pnpar, which will produce identical numerical results but label variables as Pr(participation) and Pr(nonparticipation) instead of Pr(susceptible) and Pr(nonsusceptible).

#### Example 1: Average marginal effect of gender on probability of nonsusceptibility

In example 1 of [R] ziologit, we fit a model for levels of cigarette consumption.

```
. use https://www.stata-press.com/data/r18/tobacco
(Fictional tobacco consumption data)
. ziologit tobacco education income age i.female,
> inflate(education income age i.female i.parent i.religion)
 (output omitted)
```

This model parallels the zero-inflated ordered probit (ZIOP) model that was fit in example 1 of [R] zioprobit.

To continue the comparison between the ZIOL and ZIOP models, we re-create example 1 from [R] zioprobit postestimation by using margins to estimate the average marginal effect of gender on the probability of nonsusceptibility (being an excess zero) for individuals with a college degree (17 years of education) and a smoking parent.

```
. margins, predict(pns) dydx(female) at(education = 17 parent = 1)
Average marginal effects
                                                         Number of obs = 15,000
Model VCE: OIM
Expression: Pr(nonsusceptible), predict(pns)
dv/dx wrt: 1.female
At: education = 17
    parent
                           Delta-method
                                                 P>|z|
                                                            [95% conf. interval]
                    dy/dx
                             std. err.
                                            z
      female
```

Note: dy/dx for factor levels is the discrete change from the base level.

.010096

Despite the differences between the ZIOL and ZIOP models, the conclusion is the same: women with a college degree and a smoking parent are expected to have an approximately 8.5% higher chance of being genuine nonsmokers (excess zeros) than comparable men.

8.46

0.000

.0656333

.1052087

#### 4

## Example 2: Predicted probabilities of conditional zeros

.085421

Female

Next, we consider the effect of income on the probability of zero tobacco consumption, conditional on susceptibility. These would-be smokers are known as conditional zeros. In example 1 of [R] ziologit, we saw that increasing income raises a smoker's odds of increased tobacco consumption dramatically, so we expect to see a larger fraction of conditional zeros at the lower end of the income scale.

We examine conditional probabilities of zero consumption for incomes ranging from \$10,000 to \$60,000, and we use the noatlegend option to suppress the default legend because we know the values 1 to 6 correspond to income in tens of thousands of dollars.

. margins, predict(pcond1 outcome(0)) at(income = (1/6)) noatlegend

Predictive margins Number of obs = 15,000

Model VCE: OIM

Expression: Pr(tobacco=0|susceptible=1), predict(pcond1 outcome(0))

	Margin	Delta-method std. err.	l z	P> z	[95% conf.	interval]
1	.5923634	.0027586	214.73	0.000	.5869566	.5977702
2	.5393818	.0025948	207.87	0.000	.534296	.5444676
3	. 4854668	.0024651	196.94	0.000	.4806354	.4902982
4	. 4306299	.0023953	179.78	0.000	.4259352	.4353245
5	.3741538	.0024547	152.42	0.000	.3693427	.3789649
6	.3152985	.0026294	119.91	0.000	.3101449	.320452

The influence of income is dramatic: susceptible individuals (potential smokers) who earn \$10,000 a year are almost twice as likely to refrain from smoking as potential smokers who earn \$60,000 per year (59% versus 32%).

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#### Methods and formulas

See *Methods and formulas* in [R] **ziologit** for the model definition and notation. Specifically, see (1) for the formula for the probability of susceptibility,  $\Pr(s_j = 1 | \mathbf{z}_j)$ ; see (2) for the formula for the probabilities of outcome levels conditional on susceptibility,  $\Pr(y_j = h | s_j = 1, \mathbf{x}_j)$ ; and see (4) for the formula for the marginal probabilities of outcome levels,  $\Pr(y_j = h | \mathbf{z}_j, \mathbf{x}_j)$ .

The joint probability of susceptibility and outcome  $y_j = h$  can be expressed as

$$\Pr(y_j = h, s_j = 1 | \mathbf{z}_j, \mathbf{x}_j) = \Pr(s_j = 1 | \mathbf{z}_j) \Pr(y_j = h | s_j = 1, \mathbf{x}_j)$$

for h = 0, 1, ..., H.

#### Reference

Kelley, M. E., and S. J. Anderson. 2008. Zero inflation in ordinal data: Incorporating susceptibility to response through the use of a mixture model. *Statistics in Medicine* 27: 3674–3688. https://doi.org/10.1002/sim.3267.

# Also see

[R] ziologit — Zero-inflated ordered logit regression

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

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