**Postestimation commands**

The following postestimation commands are available after `zioprobit`:

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<td>estat summarize</td>
<td>summary statistics for the estimation sample</td>
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<td>variance–covariance matrix of the estimators (VCE)</td>
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<td>point estimates, standard errors, testing, and inference for linear combinations of coefficients</td>
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<td>predictions, residuals, influence statistics, and other diagnostic measures</td>
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<td>point estimates, standard errors, testing, and inference for generalized predictions</td>
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<tr>
<td>pwcompare</td>
<td>pairwise comparisons of estimates</td>
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<td>suest</td>
<td>seemingly unrelated estimation</td>
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<tr>
<td>test</td>
<td>Wald tests of simple and composite linear hypotheses</td>
</tr>
<tr>
<td>testnl</td>
<td>Wald tests of nonlinear hypotheses</td>
</tr>
</tbody>
</table>

*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* | newvar_reg newvar_infl newvar0 ... newvar_{H-1} }
[if] [in] , scores

statistic Description

Main

_pmargin_ marginal probabilities of levels, Pr(y_j = h); the default
_pjoint1 _joint probabilities of levels and participation, Pr(y_j = h, s_j = 1)
_pcond1_ probabilities of levels conditional on participation, Pr(y_j = h | s_j = 1)
_ppar_ probability of participation, Pr(s_j = 1)
_pnpar_ probability of nonparticipation, 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_ (with one new variable specified) assumes 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 _ppar_, _pnpar_, _xb_, _xbinfl_, _stdep_, and _stdepinfl_.
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

_pmargin_, the default, calculates the predicted marginal probabilities, Pr(y_j = h).
_pjoint1_ calculates the predicted joint probabilities of outcome levels and participation, Pr(y_j = h, s_j = 1).
pcond1 calculates the predicted probabilities of outcome levels conditional on participation, \( \Pr(y_j = h|s_j = 1) \).

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(#k) option to obtain probabilities for the \( k \)th 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).

ppar calculates the predicted marginal probability of participation, \( \Pr(s_j = 1) \).

pnpar calculates the predicted marginal probability of nonparticipation, \( \Pr(s_j = 0) \).

xb calculates the linear prediction for the regression equation, which is \( x_j \beta \) if offset() was not specified with zioprobit and is \( x_j \beta + \text{offset}_j \beta \) if offset() was specified.

xbinfl calculates the linear prediction for the inflation equation, which is \( z_j \gamma \) if offset() was not specified in inflate() and is \( z_j \gamma + \text{offset}_j \gamma \) if offset() was specified in inflate().

stdp calculates the standard error of the linear prediction for the regression equation.

stdpinfl 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 zioprobit or within the inflate() option. It modifies the calculations made by predict so that they ignore the offset variable; for example, the linear prediction for the regression equation is treated as \( x_j \beta \) rather than as \( x_j \beta + \text{offset}_j \beta \).

scores calculates equation-level score variables.

The first new variable, newvarreg, will contain \( \partial \ln L / \partial (x_j \beta) \).

The second new variable, newvarinfl, will contain \( \partial \ln L / \partial (z_j \gamma) \).

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 ]

<table>
<thead>
<tr>
<th>statistic</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>pmargin</td>
<td>marginal probabilities of levels, Pr(yj = h); the default</td>
</tr>
<tr>
<td>pjoint1</td>
<td>joint probabilities of levels and participation, Pr(yj = h, sj = 1)</td>
</tr>
<tr>
<td>pcond1</td>
<td>probabilities of levels conditional on participation, Pr(yj = h</td>
</tr>
<tr>
<td>ppar</td>
<td>probability of participation, Pr(sj = 1)</td>
</tr>
<tr>
<td>pnpar</td>
<td>probability of nonparticipation, Pr(sj = 0)</td>
</tr>
<tr>
<td>xb</td>
<td>linear prediction</td>
</tr>
<tr>
<td>xbinfl</td>
<td>linear prediction for inflate equation</td>
</tr>
<tr>
<td>stdp</td>
<td>not allowed with margins</td>
</tr>
<tr>
<td>stdpinfl</td>
<td>not allowed with margins</td>
</tr>
</tbody>
</table>

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

Various sets of predictions and marginal effects may be of interest for the ZIOP model. For instance, we may want to investigate the marginal effects of a covariate on the probability of participation, or on the probabilities for levels of consumption conditional on participation, or on the overall probabilities for different consumption levels. We explore these options in greater detail in the following examples.

Example 1: Average marginal effects on probability of nonparticipation

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

```
. use https://www.stata-press.com/data/r16/tobacco
(Fictional tobacco consumption data)
. zioprobit tobacco education income i.female age,
> inflate(education income i.parent age i.female i.religion)
(output omitted)
```

We can use margins to estimate the expected marginal effect of gender for individuals with a college degree (17 years of education) and a smoking parent on the probability of nonparticipation (being a genuine nonsmoker). To do this, we specify predict(pnpar) with margins as follows:

```
. margins, predict(pnpar) dydx(female) at(education = 17 parent = 1)
Average marginal effects Number of obs = 15,000
Model VCE : OIM
Expression : Pr(nonparticipation), predict(pnpar)
dy/dx w.r.t. : 1.female
at : education = 17
    parent = 1
```

```
|            | dy/dx | Std. Err. | z     | P>|z| | 95% Conf. Interval |
|------------|-------|-----------|-------|------|-------------------|
| female     | 0.0856 | 0.0100    | 8.54  | 0.000| -0.0659 to 0.0524  |
```

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

Women with a college degree and a smoking parent are expected to have about an 8.5% higher chance of being genuine nonsmokers than do men.

Example 2: Predicted probabilities of zero-valued outcomes

In example 1 of [R] zioprobit, we found that the coefficient on income was positive in the level equation but negative in the participation equation. In the case of our tobacco consumption example, economic theory offers a reasonable interpretation for this. Higher income may act as an indicator for health awareness, which accounts for its association with an increased probability of being a genuine nonsmoker. However, if cigarettes are a normal good—that is, something for which demand increases when income increases—then smokers with higher income should have a lower probability of having zero consumption at the time of the survey.

We first consider the effect of income at six prespecified values ranging from $10,000 to $60,000 on the probability of being a genuine nonsmoker (nonparticipation). Because we know the values 1 to 6 correspond to income in tens of thousands, we conserve space and suppress the default legend by using the noatlegend option.
. margins, predict(pnpar) at(income = (1/6)) noatlegend

Predictive margins Number of obs = 15,000
Model VCE : OIM
Expression : Pr(nonparticipation), predict(pnpar)

<table>
<thead>
<tr>
<th></th>
<th>Delta-method</th>
<th></th>
<th></th>
<th></th>
<th>[95% Conf. Interval]</th>
</tr>
</thead>
<tbody>
<tr>
<td>_at</td>
<td>Margin</td>
<td>Std. Err.</td>
<td>z</td>
<td>P&gt;</td>
<td>z</td>
</tr>
<tr>
<td>1</td>
<td>0.1727928</td>
<td>0.0056963</td>
<td>30.33</td>
<td>0.000</td>
<td>0.1616283 - 0.1839573</td>
</tr>
<tr>
<td>2</td>
<td>0.1944564</td>
<td>0.0055236</td>
<td>35.20</td>
<td>0.000</td>
<td>0.1836304 - 0.2052824</td>
</tr>
<tr>
<td>3</td>
<td>0.2176878</td>
<td>0.0052981</td>
<td>41.09</td>
<td>0.000</td>
<td>0.2072945 - 0.2280629</td>
</tr>
<tr>
<td>4</td>
<td>0.2424141</td>
<td>0.0050413</td>
<td>48.09</td>
<td>0.000</td>
<td>0.2325333 - 0.2522948</td>
</tr>
<tr>
<td>5</td>
<td>0.2685948</td>
<td>0.0047857</td>
<td>56.12</td>
<td>0.000</td>
<td>0.259215 - 0.2779745</td>
</tr>
<tr>
<td>6</td>
<td>0.2961309</td>
<td>0.0045767</td>
<td>64.70</td>
<td>0.000</td>
<td>0.2871607 - 0.3051011</td>
</tr>
</tbody>
</table>

The probability of being a genuine nonsmoker increases with income. For instance, for individuals who earn $10,000 a year, the expected increase in the probability of being a genuine nonsmoker is about \((0.1945 - 0.1728) \times 100\% = 2.17\%\) if they earn an additional $10,000.

We next investigate the effect of income on the joint probability of being a smoker (participation equals 1) with zero consumption. We do this by specifying *predict(pjoint1 outcome(0))* with *margins*:

. margins, predict(pjoint1 outcome(0)) at(income = (1/6)) noatlegend

Predictive margins Number of obs = 15,000
Model VCE : OIM
Expression : Pr(tobacco=0, participation=1), predict(pjoint1 outcome(0))

<table>
<thead>
<tr>
<th></th>
<th>Delta-method</th>
<th></th>
<th></th>
<th></th>
<th>[95% Conf. Interval]</th>
</tr>
</thead>
<tbody>
<tr>
<td>_at</td>
<td>Margin</td>
<td>Std. Err.</td>
<td>z</td>
<td>P&gt;</td>
<td>z</td>
</tr>
<tr>
<td>1</td>
<td>0.5595131</td>
<td>0.0040167</td>
<td>139.30</td>
<td>0.000</td>
<td>0.5516405 - 0.5673856</td>
</tr>
<tr>
<td>2</td>
<td>0.5080066</td>
<td>0.0037793</td>
<td>134.42</td>
<td>0.000</td>
<td>0.5005993 - 0.5154139</td>
</tr>
<tr>
<td>3</td>
<td>0.4558656</td>
<td>0.0035553</td>
<td>128.22</td>
<td>0.000</td>
<td>0.4488975 - 0.4628338</td>
</tr>
<tr>
<td>4</td>
<td>0.4029089</td>
<td>0.0033683</td>
<td>119.62</td>
<td>0.000</td>
<td>0.3963072 - 0.4095106</td>
</tr>
<tr>
<td>5</td>
<td>0.3485692</td>
<td>0.0032481</td>
<td>107.32</td>
<td>0.000</td>
<td>0.3422031 - 0.3549352</td>
</tr>
<tr>
<td>6</td>
<td>0.2929155</td>
<td>0.00317</td>
<td>92.40</td>
<td>0.000</td>
<td>0.2867023 - 0.2991287</td>
</tr>
</tbody>
</table>

For individuals who are smokers, the probability of zero consumption decreases as income increases, suggesting that tobacco is like a normal good for smokers. For example, for individuals who earn $10,000 a year, earning an additional $10,000 will decrease their probability of being a smoker with zero consumption by about \((0.5595 - 0.5080) \times 100\% = 5.15\%\).

If we wanted to compute the effect of income on the overall probability of zero consumption instead of the probability of zero consumption among smokers, we would omit *pjoint1* from within the *predict* option.

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

(output omitted)

This version of the *margins* command gives the sum of the probability of nonparticipation and the joint probability of participation with zero consumption.
Methods and formulas

The participation equation is

\[ s_j = I(z_j \gamma + u_{1j} > 0) \quad j = 1, 2, \ldots, n \]

where \( s_j \) is 1 if the \( j \)th subject belongs to the participation group (for example, smokers) and is 0 if the subject belongs to the nonparticipation group (for example, genuine nonsmokers), \( z_j \) are the covariates used to model the group membership, \( \gamma \) is a vector of coefficients, and \( u_{1j} \) is a random-error term following a standard normal distribution.

The ordinal outcome equation is

\[ \tilde{y}_j = \sum_{h=0}^{H} hI(\kappa_{h-1} < x_j \beta + u_{2j} \leq \kappa_h) \]

where \( \tilde{y}_j \) is the ordinal outcome conditional on participation, \( x_j \) are the outcome covariates, \( \beta \) are the coefficients, and \( u_{2j} \) is a random-error term following a standard normal distribution. The observed outcome values are 0, 1, \ldots, \( H \). \( \kappa_0, \kappa_1, \ldots, \kappa_{H-1} \) are real numbers such that \( \kappa_i < \kappa_m \) for \( i < m \). \( \kappa_{-1} \) is taken as \(-\infty\) and \( \kappa_H \) is taken as \(+\infty\). We assume that the error terms \( u_{1j} \) and \( u_{2j} \) are independent. We observe \( y_j = s_j \tilde{y}_j \).

The probability of participation is

\[ \Pr(s_j = 1|z_j) = \Phi(z_j \gamma) \quad (1) \]

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

The probability of nonparticipation is

\[ \Pr(s_j = 0|z_j) = 1 - \Phi(z_j \gamma) \quad (2) \]

The probability of outcome \( y_j = h \) given that the \( j \)th subject belongs to the participation group is

\[ \Pr(y_j = h|s_j = 1, x_j) = \Pr(\tilde{y}_j = h|x_j) = \Phi(\kappa_h - x_j \beta) - \Phi(\kappa_{h-1} - x_j \beta) \quad (3) \]

for \( h = 0, 1, \ldots, H \), where \( \Phi(\kappa_{-1} - x_j \beta) = 0 \) and \( \Phi(\kappa_H - x_j \beta) = 1 \).

The joint probability of outcome \( y_j = h \) and participation can be expressed as

\[ \Pr(y_j = h, s_j = 1|z_j, x_j) = \Pr(s_j = 1|z_j) \Pr(y_j = h|s_j = 1, x_j) \]

for \( h = 0, 1, \ldots, H \), and computed using (1) and (3).

The marginal probabilities of the outcome \( y_j \) are

\[ \Pr(y_j = 0|z_j, x_j) = \Pr(s_j = 0|z_j) + \Pr(s_j = 1|z_j) \Pr(\tilde{y}_j = 0|x_j) \]

\[ \Pr(y_j = h|z_j, x_j) = \Pr(s_j = 1|z_j) \Pr(\tilde{y}_j = h|x_j) \quad h = 1, 2, \ldots, H - 1 \]

\[ \Pr(y_j = H|z_j, x_j) = \Pr(s_j = 1|z_j) \Pr(\tilde{y}_j = H|x_j) \]

and can be computed using (1), (2), and (3).

If the \texttt{offset()} option is specified with \texttt{zioprobit}, \( x_j \beta \) is replaced with \( x_j \beta + \text{offset}_j \). If the \texttt{offset()} option is specified within the \texttt{inflate()} option, \( z_j \gamma \) is replaced with \( z_j \gamma + \text{offset}_j \).

Also see

[R] \texttt{zioprobit} — Zero-inflated ordered probit regression

[U] 20 Estimation and postestimation commands