eoprobit postestimation — Postestimation tools for eoprobit

Postestimation commands

The following postestimation command is of special interest after `eoprobit`:

Command	Description
`estat teffects`	treatment effects and potential-outcome means

The following standard postestimation commands are also available after `eoprobit`:

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
* `forecast`	dynamic forecasts and simulations
`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`	predictions, residuals, influence statistics, 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

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

predict

Predictions after `eoprobit` are described in

[ERM] **eoprobit predict**	predict after eoprobit
[ERM] **predict treatment**	predict for treatment statistics
[ERM] **predict advanced**	predict's advanced features

[ERM] **eoprobit predict** describes the most commonly used predictions. If you fit a model with treatment effects, predictions specifically related to these models are detailed in [ERM] **predict treatment**. [ERM] **predict advanced** describes less commonly used predictions, such as predictions of outcomes in auxiliary equations.

margins

Description for margins

`margins` estimates margins of response for probabilities, means, potential-outcome means, treatment effects, and linear predictions.

Menu for margins

Statistics > Postestimation

Syntax for margins

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

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

statistic	Description
Main	
`pr`	probability for binary or ordinal y_j; the default
`mean`	mean
`pomean`	potential-outcome mean
`te`	treatment effect
`tet`	treatment effect on the treated
`xb`	linear prediction
`pr(`*a*,*b*`)`	$\Pr(a < y_j < b)$ for continuous y_j
`e(`*a*,*b*`)`	$E(y_j \mid a < y_j < b)$ for continuous y_j
`ystar(`*a*,*b*`)`	$E(y_j^*)$, $y_j^* = \max\{a, \min(y_j, b)\}$ for continuous y_j

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

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

Remarks and examples

stata.com

See [ERM] **intro 6** for an overview of using `margins` and `predict` after `eoprobit`. For examples using `margins`, `predict`, and `estat teffects`, see *Interpreting effects* in [ERM] **intro 8** and see [ERM] **example 1a**.

Methods and formulas

This section contains methods and formulas for counterfactual predictions and inference. Methods and formulas for all other predictions are given in *Methods and formulas* of [ERM] **eoprobit**. In *Methods and formulas* of [ERM] **eoprobit**, we discussed how treatment effects are evaluated in extended ordered probit regression models. Here, we discuss the counterfactual framework used to evaluate the effects of other covariates.

In the extended ordered probit regression model for y_i on exogenous covariates $\mathbf{x}_i$ and $\mathbf{w}_i$, we partition each set of covariates into two groups. The exogenous covariates $\mathbf{x}_i$ are partitioned into $\mathbf{x}_i^c$ and $\mathbf{x}_i^{nc}$, where we are interested in the effect of changes in $\mathbf{x}_i^c$. Similarly, the endogenous covariates $\mathbf{w}_i$ are partitioned into $\mathbf{w}_i^c$ and $\mathbf{w}_i^{nc}$, where the effect of changes in $\mathbf{w}_i^c$ is of interest. The superscripts indicate what is a counterfactual value (c) and what is not (nc).

If $\mathbf{x}_i^c = \mathbf{a}_0$ and $\mathbf{w}_i^c = \mathbf{a}_{20}$, for covariates $\mathbf{w}_i^{nc}$ and $\mathbf{x}_i^{nc}$ we would observe the outcome

$$y_{0i} = v_h \quad \text{iff} \quad \kappa_{h-1} < \boldsymbol{\beta}_{0nc}\mathbf{x}_i^{nc} + \boldsymbol{\beta}_{20nc}\mathbf{w}_i^{nc} + \boldsymbol{\beta}_c\mathbf{a}_0 + \boldsymbol{\beta}_{2c}\mathbf{a}_{20} + \epsilon_{0i} \leq \kappa_h$$

The values $v_1, \dots, v_H$ are real numbers such that $v_h < v_m$ for $h < m$. κ_0 is taken as $-\infty$ and κ_H is taken as $+\infty$. Where the unobserved error ϵ_{0i} is standard normal. We treat $\boldsymbol{\beta}_c\mathbf{a}_0 + \boldsymbol{\beta}_{2c}\mathbf{a}_{20} = \beta_{c0}$ as a constant intercept, because it is the same for each value combination of the covariates $\mathbf{w}_i^{nc}$ and $\mathbf{x}_i^{nc}$ and the error ϵ_{0i}.

Similarly, if $\mathbf{x}_i^c = \mathbf{a}_1$ and $\mathbf{w}_i^c = \mathbf{a}_{21}$, for covariates $\mathbf{w}_i^{nc}$ and $\mathbf{x}_i^{nc}$ we would observe the outcome

$$y_{1i} = v_h \quad \text{iff} \quad \kappa_{h-1} < \boldsymbol{\beta}_{1nc}\mathbf{x}_i^{nc} + \boldsymbol{\beta}_{21nc}\mathbf{w}_i^{nc} + \boldsymbol{\beta}_c\mathbf{a}_1 + \boldsymbol{\beta}_{2c}\mathbf{a}_{21} + \epsilon_{1i} \leq \kappa_h$$

To define the effects, for $j = 0, 1$ and $h = 1, \dots, H$, we can examine the variables

$$y_{jhi} = \begin{cases} 1 & \text{if } y_{ji} = v_h \\ 0 & \text{if } y_{ji} \neq v_h \end{cases}$$

The effect of changing $\mathbf{x}_i^c$ and $\mathbf{w}_i^c$ from $\mathbf{a}_0$ and $\mathbf{a}_{20}$ to $\mathbf{a}_1$ and $\mathbf{a}_{21}$ on the probability that $y_i = v_h$ is the expected difference between $\mathbf{y}_{1hi}$ and $\mathbf{y}_{0hi}$.

To obtain this difference, we average the conditional probabilities of $\mathbf{y}_{1hi}$ and $\mathbf{y}_{0hi}$ as a predictive margin.

For $j = 0, 1$ and $h = 1, \dots, H$, we can predict the counterfactual probability for group j using the tools discussed in *Predictions using the full model* in [ERM] **eprobit postestimation**:

$$\text{CP}_{jh}(\mathbf{w}_i^{nc}, \mathbf{x}_i^{nc}, \mathbf{z}_i) = \Pr(y_{jhi} = 1 | \mathbf{w}_i^{nc}, \mathbf{x}_i^{nc}, \mathbf{x}_i^c = \mathbf{a}_j, \mathbf{z}_i)$$

where $\mathbf{z}_i$ are instruments necessary for modeling the endogenous regressors $\mathbf{w}_i^{nc}$. By the law of iterated expectations, we have

$$E(y_{1hi} - y_{0hi}) = E\left\{\text{CP}_{1h}(\mathbf{w}_i^{nc}, \mathbf{x}_i^{nc}, \mathbf{z}_i)\right\} - E\left\{\text{CP}_{0h}(\mathbf{w}_i^{nc}, \mathbf{x}_i^{nc}, \mathbf{z}_i)\right\}$$

So the effect of changing $\mathbf{x}_i^c$ and $\mathbf{w}_i^c$ from $\mathbf{a}_0$ and $\mathbf{a}_{20}$ to $\mathbf{a}_1$ and $\mathbf{a}_{21}$ can be estimated as a predictive margin on the counterfactual probabilities.

We can use `predict` with the `fix()` and `target()` options to predict the counterfactual probabilities. The `fix()` option is used to indicate the endogenous covariates in $\mathbf{w}_i^c$. The `target()` option can be used to set the counterfactual values a_j and a_{2j} of $\mathbf{x}_i^c$ and $\mathbf{w}_i^c$.

When $\mathbf{w}_i^c$ corresponds to a single ordinal or binary regressor, the difference in counterfactual probabilities corresponds to a treatment effect of $\mathbf{w}_i^c$. We can also evaluate the effect of a change in $\mathbf{w}_i^c$ and $\mathbf{x}_i^c$, conditioned on $\mathbf{w}_i^c$. This effect is analogous to the treatment effect on the treated discussed in *Methods and formulas* of [ERM] **eoprobit**. We are conditioning the effect on some base value for $\mathbf{w}_i^c$, $\mathbf{w}_i^c = \mathbf{b}$.

Now, the counterfactual probabilities are conditioned on $\mathbf{w}_i^c = \mathbf{b}$. So for $j = 0, 1$ and $h = 1, \ldots, H$, we have

$$\text{CP}_{bjh}(\mathbf{w}_i^{nc}, \mathbf{b}, \mathbf{x}_i^{nc}, \mathbf{z}_i) = \Pr(y_{jhi} = 1 | \mathbf{w}_i^{nc}, \mathbf{w}_i^c = \mathbf{b}, \mathbf{x}_i^{nc}, \mathbf{x}_i^c = \mathbf{a}_j, \mathbf{z}_{bi})$$

where $\mathbf{z}_{bi}$ are instruments necessary for modeling the endogenous regressors $\mathbf{w}_i^{nc}$ and $\mathbf{w}_i^c$. This counterfactual probability can be evaluated using the tools discussed in *Predictions using the full model* in [ERM] **eprobit postestimation**.

By the law of iterated expectations, we have

$$\begin{aligned} E(y_{1hi} - y_{0hi} | \mathbf{w}_i^c = \mathbf{b}) = & E\left\{\text{CP}_{b1h}(\mathbf{w}_i^{nc}, \mathbf{w}_i^c = \mathbf{b}, \mathbf{x}_i^{nc}, \mathbf{z}_i) | \mathbf{w}_i^c = \mathbf{b}\right\} - \\ & E\left\{\text{CP}_{b0h}(\mathbf{w}_i^{nc}, \mathbf{w}_i^c = \mathbf{b}, \mathbf{x}_i^{nc}, \mathbf{z}_i) | \mathbf{w}_i^c = \mathbf{b}\right\} \end{aligned}$$

So the effect of changing $\mathbf{x}_i^c$ and $\mathbf{w}_i^c$ from $\mathbf{a}_0$ and $\mathbf{a}_{20}$ to $\mathbf{a}_1$ and $\mathbf{a}_{21}$ conditioned on $\mathbf{w}_i^c = \mathbf{b}$ can be estimated as a predictive margin on the counterfactual probabilities.

The base values $\mathbf{b}$ for $\mathbf{w}_i^c$ are specified in the `base()` option. As before, `target()` can be used to specify the counterfactual values for $\mathbf{x}_i^c$ and $\mathbf{w}_i^c$.

When $\mathbf{x}_i^c = \mathbf{x}_i$ and $\mathbf{w}_i^c = \mathbf{w}_i$, the counterfactual probability matches the average structural probability (ASP). Applying the average structural function (ASF) discussed by Blundell and Powell (2003), Blundell and Powell (2004), Wooldridge (2005), and Wooldridge (2014) to a conditional probability on the covariates and unobserved endogenous error produces the ASP.

In the ordered probit model, for exogenous covariates $\mathbf{x}_i$ and endogenous regressors $\mathbf{w}_i$, we have

$$y_i = v_h \quad \text{iff} \quad \kappa_{h-1} < \mathbf{x}_i\boldsymbol{\beta} + \mathbf{w}_i\boldsymbol{\beta}_2 + \epsilon_i \leq \kappa_h$$

The values $v_1, \ldots, v_H$ are real numbers such that $v_h < v_m$ for $h < m$. κ_0 is taken as $-\infty$ and κ_H is taken as $+\infty$. The error ϵ_i is standard normal and correlated with $\mathbf{w}_i$.

The ASP provides a structural interpretation of $\boldsymbol{\beta}$ and $\boldsymbol{\beta}_2$ when the $\mathbf{w}_i$ are correlated with ϵ_i. Because ϵ_i is a normally distributed, mean 0, random variable, we can split it into two mean 0, normally distributed, independent parts,

$$\epsilon_i = u_i + \psi_i$$

where $u_i = \boldsymbol{\gamma}\boldsymbol{\epsilon}_{2i}$ is the unobserved heterogeneity that gives rise to the endogeneity and ψ_i is an error term with variance σ_ψ^2.

For $h = 0, \ldots, H$, define

$$c_{ih} = \begin{cases} -\infty & h = 0 \\ \kappa_h - \mathbf{x}_i\boldsymbol{\beta} - \mathbf{w}_i\boldsymbol{\beta}_2 - u_i & h = 1, \ldots, H-1 \\ \infty & h = H \end{cases}$$

Conditional on the covariates and the unobserved heterogeneity, we have

$$E\{\mathbf{1}(y_i = v_h)|\mathbf{x}_i, \mathbf{w}_i, u_i\} = \Pr(y_i = v_h|\mathbf{x}_i, \mathbf{w}_i, u_i)$$
$$= \Phi_1^*(c_{i(h-1)}, c_{ih}, \sigma_\psi^2)$$

Because u_i is an unobserved random variable, these conditional probabilities are not observable. Integrating out the u_i, just like we do with random effects in panel-data models, produces the ASP for each category,

$$\text{ASP}_h(\mathbf{x}_i^0, \mathbf{w}_i^0) = \int E\{\mathbf{1}(y_i = v_h)|\mathbf{x}_i^0, \mathbf{w}_i^0, u_i\} f(u_i)\, du_i$$

where $f(u_i)$ is the marginal distribution of u_i, and $\mathbf{x}_i^0$ and $\mathbf{w}_i^0$ are given covariate values.

References

Blundell, R. W., and J. L. Powell. 2003. Endogeity in nonparametric and semiparametric regression models. In *Advances in Economics and Econometrics: Theory and Applications, Eighth World Congress*, ed. M. Dewatripont, L. P. Hansen, and S. J. Turnovsky, vol. 2, 312–357. Cambridge: Cambridge University Press.

——. 2004. Endogeneity in semiparametric binary response models. *Review of Economic Studies* 71: 655–679.

Wooldridge, J. M. 2005. Unobserved heterogeneity and estimation of average partial effects. In *Identification and Inference for Econometric Models: Essays in Honor of Thomas Rothenberg*, ed. D. W. K. Andrews and J. H. Stock, 27–55. New York: Cambridge University Press.

——. 2014. Quasi-maximum likelihood estimation and testing for nonlinear models with endogenous explanatory variables. *Journal of Econometrics* 182: 226–234.

Also see

[ERM] **eoprobit** — Extended ordered probit regression

[ERM] **eoprobit predict** — predict after eoprobit

[ERM] **predict treatment** — predict for treatment statistics

[ERM] **predict advanced** — predict's advanced features

[ERM] **eprobit postestimation** — Postestimation tools for eprobit

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