Description

xtheckman fits a random-effects linear regression model with endogenous sample selection.

Quick start

Random-effects model of \( y \) on \( x_1 \) using \texttt{xtset} data, with selection indicated by binary variable \texttt{selected} and predicted by \texttt{v1} and \( x_1 \)

\begin{verbatim}
xtheckman y x1, select(selected = v1 x1)
\end{verbatim}

As above, but constraining random effects to be independent

\begin{verbatim}
xtheckman y x1, select(selected = v1 x1) norecorrelation
\end{verbatim}

As above, but omit random effects from selection model

\begin{verbatim}
xtheckman y x1, select(selected = v1 x1, nore)
\end{verbatim}

Menu

Statistics \rightarrow Longitudinal/panel data \rightarrow Sample-selection models \rightarrow Linear regression with sample selection (RE)
## Syntax

```
xcheckman  depvar  [ indepvars ]  [ if ]  [ in ],
select( depvar_s = varlist_s ,  sel_options )  [ options ]
```

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### Model

- **noconstant** suppress constant term
- **nore** do not include random effects in selection model
- **offset(varname_o)** include varname_o in model with coefficient constrained to 1

*select() is required.

- **indepvars** and **varlist_s** may contain factor variables; see [U] 11.4.3 Factor variables.
- **depvar**, **indepvars**, **depvar_s**, and **varlist_s** may contain time-series operators; see [U] 11.4.4 Time-series varlists.
- bootstrap, by, jackknife, and statsby are allowed. See [U] 11.1.10 Prefix commands.
- collinear and coeflegend do not appear in the dialog box.

See [U] 20 Estimation and postestimation commands for more capabilities of estimation commands.
Options

\texttt{select(\textit{depvar} = \textit{varlist} , \textit{sel_options})\texttt{}} specifies a random-effects probit model for sample selection with \textit{varlist} as the covariates for the selection model. When \textit{depvar} = 1, the model’s dependent variable is treated as observed (selected); when \textit{depvar} = 0, it is treated as unobserved (not selected). \texttt{select(\texttt{)}} is required.

\textit{sel_options} are the following:

- \texttt{nocconstant} suppresses the constant term (intercept) in the selection model.
- \texttt{nore} specifies that a random effect not be included in the selection equation.
- \texttt{offset(\textit{varname} o\texttt{)}} specifies that \textit{varname} o be included in the selection model with the coefficient constrained to 1.

\texttt{nocconstant}; see \cite{R} Estimation options.

\texttt{norecorrelation} constrains the random effects in the outcome and selection equations to be independent.

\texttt{offset(\textit{varname} o\texttt{)}, constraints(\textit{numlist})\texttt{}}; see \cite{XT} vce options.

\texttt{vce(\textit{vcetype})\texttt{}} specifies the type of standard error reported, which includes types that are derived from asymptotic theory (\texttt{oim}, \texttt{opg}), that are robust to some kinds of misspecification (\texttt{robust}), that allow for intragroup correlation (\texttt{cluster clustvar}), and that use bootstrap or jackknife methods (\texttt{bootstrap, jackknife}); see \cite{XT} vce options.

\texttt{level(\#), nocnsreport}; see \cite{R} Estimation options.

\texttt{display_options: noci, nopvalues, noomitted, vsquish, noemptycells, baselevels, allbaselevels, nofvlabel, fvwrap(\#), fvwrapon(style), cformat(\%fmt), pformat(\%fmt), sformat(\%fmt), and nolstretch}; see \cite{R} Estimation options.

\texttt{intmethod(intmethod)\texttt{}} and \texttt{intpoints(\#)\texttt{}} control how the integration of random effects is numerically calculated.

\texttt{intmethod(\texttt{)}} specifies the integration method. The default method is mean-variance adaptive Gauss–Hermite quadrature, \texttt{intmethod\textbackslash mvaghermite}. We recommend this method. \texttt{intmethod(ghermite)} specifies that nonadaptive Gauss–Hermite quadrature be used. This method is less computationally intensive and less accurate. It is sometimes useful to try \texttt{intmethod(ghermite)} to get the model to converge and then perhaps use the results as initial values specified in option \texttt{from} when fitting the model using the more accurate \texttt{intmethod\textbackslash mvaghermite}. See \textit{Methods and formulas} for more details.

\texttt{intpoints(\#)} sets the number of integration (quadrature) points used for integration of the random effects. The default is \texttt{intpoints(7)}\texttt{). Increasing the number increases accuracy but also increases computational time. Computational time is roughly proportional to the number specified. See \textit{Methods and formulas} for more details.
**Remarks and examples**

`xtheckman` fits a panel-data model with endogenous sample selection. Endogenous sample selection is sometimes called nonignorability of selection, missing not at random, or selection bias. Within-panel correlation is accounted for by using panel-level random effects.

The outcome of interest \( y_{it} \) is modeled as

\[
y_{it} = x_{it} \beta + \nu_{1i} + \epsilon_{1it}
\]

where \( x_{it} \) are the covariates modeling the outcome, \( \nu_{1i} \) is the panel-level random effect, and \( \epsilon_{1it} \) is the observation-level error.

We model the selection process for the outcome by

\[
s_{it} = 1 \left( z_{it} \alpha + \nu_{2i} + \epsilon_{2it} > 0 \right)
\]

where \( s_{it} = 1 \) if we observe \( y_{it} \) and 0 otherwise, \( z_{it} \) are the covariates modeling selection, \( \nu_{2i} \) is the panel-level random effect for selection, and \( \epsilon_{2it} \) is the observation-level selection error.

The random effects \( \nu_{1i} \) and \( \nu_{2i} \) are bivariate normal with mean 0 and variance

\[
\begin{bmatrix}
\sigma_{\nu}^2 & \rho \sigma_\nu \sigma_{2\nu} \\
\rho \sigma_\nu \sigma_{2\nu} & \sigma_{2\nu}^2
\end{bmatrix}
\]

The observation-level errors \( \epsilon_{1it} \) and \( \epsilon_{2it} \) are bivariate normal, with mean 0 and variance

\[
\begin{bmatrix}
\sigma_1^2 & \rho \sigma_1 \\
\rho \sigma_1 & 1
\end{bmatrix}
\]

These observation-level errors are independent of the random effects.

Using the Heckman estimator (`heckman`) for this model will provide inefficient estimates because it ignores the within-panel correlation. Instead, we use maximum likelihood to model both the selection and outcome equations and account for the panel structure of the data. This random-effects estimator is used by `xteregress` and was discussed in Rabe-Hesketh, Skrondal, and Pickles (2002). There is no parametric fixed-effects estimator for panel data from an endogenously selected sample. See Honoré, Kyriazidou, and Powell (2000) and Kyriazidou (1997) for semiparametric fixed-effects estimators of panel-data endogenous sample-selection models.
Example 1

Suppose that we wish to study the relationship between wage, job tenure, and age for college-educated adults. We have fictional data on 600 adults observed from 2013 to 2016. We use these data to model hourly wage as a function of age, age squared, and job tenure. However, an individual’s wage is observed only if he or she works, and not everyone was employed on the dates the data were collected. We are not interested in modeling only the subpopulation of individuals who were employed at the time. We are also interested in the relationship of job tenure and age with the wage an individual would have received if he or she had been employed.

We suspect that the unobserved factors that affect an individual’s wage are related to the unobserved factors that affect employment status. These unobserved factors could include person-level characteristics like ability and time-varying factors like an individual’s family situation. We suspect that we have an endogenously selected sample. We have data on the local job market conditions (market). This variable is used with age and tenure to model the employment status of an individual.

Before we can fit a random-effects model to our data, we need to specify the panel structure of the data using xtset. Our panel variable is personid, the identification code for the individual. The time variable is year, and it ranges from 2013 to 2016.

```
. use https://www.stata-press.com/data/r16/wagework
   (Wages for 20 to 77 year olds, 2013-2016)
. xtset personid year
    panel variable:  personid (strongly balanced)
    time variable:   year, 2013 to 2016
    delta: 1 unit
```
We are now ready to fit our model.

```
xheckman wage c.age##c.age tenure, select (working = c.age##c.age market)
(setting technique to bhhh)
Iteration 0:  log likelihood =  -5384.5076
Iteration 1:  log likelihood =  -5377.4625
Iteration 2:  log likelihood =  -5376.4805
Iteration 3:  log likelihood =  -5376.4505
Iteration 4:  log likelihood =  -5376.4464
Iteration 5:  log likelihood =  -5376.4454
Iteration 6:  log likelihood =  -5376.4451
Iteration 7:  log likelihood =  -5376.4451
Iteration 8:  log likelihood =  -5376.4451
Iteration 9:  log likelihood =  -5376.4450
(switching technique to nr)
Iteration 10: log likelihood =  -5376.4451
```

Random-effects regression with selection

Number of obs = 2,400
Selected = 1,928
Nonselected = 472

Group variable: personid

Number of groups = 600
Obs. per group:  min = 4
                avg = 4.0
                max = 4

Integration method: mvaghermite
Integration pts. = 7

Log likelihood =  -5376.445

|                | Coef. | Std. Err. | z    | P>|z| | [95% Conf. Interval] |
|----------------|-------|-----------|------|------|----------------------|
| wage           |       |           |      |      |                      |
| age            | .5722234 | .0477613 | 11.98 | 0.000 | .4786129 .6658339    |
| c.age##c.age   | -.0042448 | .0005329 | -7.97 | 0.000 | -.0052893 -.0032003 |
| tenure         | .5927719 | .0169866 | 34.90 | 0.000 | .5594787 .626065    |
| _cons          | 5.651812 | 1.038011 | 5.44 | 0.000 | 3.617347 7.686277   |
| working        |       |           |      |      |                      |
| age            | .2305309 | .0207988 | 11.08 | 0.000 | .1897661 .2712958   |
| c.age##c.age   | -.0026832 | .0002241 | -11.97 | 0.000 | -.0031225 -.0022439 |
| market         | .1894934 | .019038  | 9.95  | 0.000 | .1521796 .2268072   |
| _cons          | -3.276904 | .4352836 | -7.53 | 0.000 | -4.130045 -2.423764 |
| var(e.wage)    | 4.458219 | .2235342 |       |      | 4.040939 4.918588   |
| corr(e.wor-g,  | .4091115 | .1391856 | 2.94  | 0.003 | .1065022 .642359    |
| e.wage)        |       |           |      |      |                      |
| var(           | 2.493737 | .2547628 |       |      | 2.041226 3.046564   |
| wage[pers-d])  |       |           |      |      |                      |
| var(           | .3831411 | .0830963 |       |      | .250466 .5860961   |
| wor-g[per-d])  |       |           |      |      |                      |
| corr(          | .6021096 | .0845675 | 7.12  | 0.000 | .4106863 .7426953   |
| wage[pers-d])  |       |           |      |      |                      |
The first two sections of the output provide the estimated coefficients for the wage equation and the selection (working) equation. We can interpret the coefficients in the wage equation using the standard linear regression interpretation. For example, we expect an increase of $0.59 per hour for an additional year of job tenure.

Next we see \( \text{var}(e.\text{wage}) \), an estimate of the variance of the observation-level error for wage; this is followed by \( \text{corr}(e.\text{working}, e.\text{wage}) \), an estimate of its correlation with the observation-level error for the selection model. The next section of the output reports estimates of the variances of the random effects, \( \text{var}(\text{wage}[\text{personid}]) \) and \( \text{var}(\text{working}[\text{personid}]) \). The last section reports an estimate of the correlation of these random effects. If at least one of the correlations is significantly different from zero, we can conclude that we have endogenous sample selection. In our case, the correlation between the observation-level errors is 0.41, and the correlation between the random effects is 0.60. Because both are positive and significantly different from zero, we conclude that we have endogenous selection and that unobserved individual-level factors that increase the chance of being employed tend to increase wage. Additionally, unobserved observation-level (time-varying) factors that increase the chance of being employed tend to increase wage.

We estimated coefficients for age and age squared. We can use \texttt{margins} and \texttt{marginsplot} to gain a clearer understanding of the effect of the individuals’ age on hourly wage. We use \texttt{margins} with \texttt{at()} to profile the expected wages for individuals between ages 30 and 70 and with 0 and 5 years of job tenure. Then, we use \texttt{marginsplot} to graph the estimates.

\[
\texttt{. margins, at(age=(30(5)70) tenure = (0 5))}
\]
\[
\texttt{. marginsplot}
\]

Based on this model, and assuming the data are from a random or otherwise representative sample, the plotted points represent the expected wage for individuals with the specified job tenure and age. We see that age has an increasing effect on expected wage until the mid-60s and then attenuates. Having 5 years of job tenure instead of none shifts the curve up by about $3.00 per hour.
xtheckman stores the following in **e()**:

### Scalars

- `e(N)` number of observations
- `e(N_g)` number of groups
- `e(N_selected)` number of selected observations
- `e(N_nonselected)` number of nonselected observations
- `e(k)` number of parameters
- `e(k_eq)` number of equations in `e(b)`
- `e(k_eq_model)` number of equations in overall model test
- `e(k_aux)` number of auxiliary parameters
- `e(k_dw)` number of dependent variables
- `e(df_m)` model degrees of freedom
- `e(ll)` log likelihood
- `e(N_clust)` number of clusters
- `e(chi2)` χ²
- `e(p)` p-value for model test
- `e(n_requad)` number of integration points for random effects
- `e(g_min)` smallest group size
- `e(g_avg)` average group size
- `e(g_max)` largest group size
- `e(rank)` rank of `e(V)`
- `e(ic)` number of iterations
- `e(rc)` return code
- `e(converged)` 1 if converged, 0 otherwise

### Macros

- `e(cmd)` xtheckman
- `e(cmdline)` command as typed
- `e(depvar)` names of dependent variables
- `e(ivar)` variable denoting groups
- `e(title)` title in estimation output
- `e(clustvar)` name of cluster variable
- `e(offset #)` offset for the #th depvar, where # is determined by equation order in output
- `e(chi2type)` Wald; type of model χ² test
- `e(vcetype)` vcetype specified in vce()
- `e(user)` name of likelihood-evaluator program
- `e(technique)` maximization technique
- `e(properties)` b V
- `e(estat_cmd)` program used to implement estat
- `e(predict)` program used to implement predict
- `e(marginsok)` predictions allowed by margins
- `e(marginsnotok)` predictions disallowed by margins
- `e(asbalanced)` factor variables fvset as asbalanced
- `e(asobserved)` factor variables fvset as asobserved

### Matrices

- `e(b)` coefficient vector
- `e(Cns)` constraints matrix
- `e(gradient)` gradient vector
- `e(V)` variance–covariance matrix of the estimators
- `e(V_modelbased)` model-based variance

### Functions

- `e(sample)` marks estimation sample
Methods and formulas

xtheckman fits a random-effects linear regression model with endogenous sample selection via maximum likelihood estimation. For details on maximum likelihood estimators, see the results in Wooldridge (2010, chap. 13) and White (1996).

The log-likelihood function maximized by xtheckman is implied by the triangular structure of the model. Specifically, the joint distribution of the outcome and selection variables is a product of conditional and marginal distributions because the model is triangular. For a few of the many relevant applications of this result in literature, see Amemiya (1985, chap. 10); Heckman (1976, 1979); Maddala (1983, chap. 5); Maddala and Lee (1976); Wooldridge (2010, sec. 15.7.2, 15.7.3, 16.3.3, 17.5.2, and 19.7.1; 2014). Roodman (2011) and Bartus and Roodman (2014) used this result to derive the formulas discussed below.

We have panels $i = 1, \ldots, N$ and observations $t = 1, \ldots, N_i$. We model $y_{it}$ as

$$y_{it} = x_{it}\beta + \nu_{1i} + \epsilon_{1it}$$

where $x_{it}$ are the outcome covariates, $\nu_{1i}$ is the panel-level random effect, and $\epsilon_{1it}$ is the observation-level error.

The selection process for the outcome is modeled by

$$s_{it} = 1 \left( z_{it}\alpha + \nu_{2i} + \epsilon_{2it} > 0 \right)$$

where $s_{it} = 1$ if we observe $y_{it}$ and 0 otherwise, $z_{it}$ are the selection covariates, $\nu_{2i}$ is the panel-level random effect for selection, and $\epsilon_{2it}$ is the observation-level selection error.

The random effects $\nu_{1i}$ and $\nu_{2i}$ are bivariate normal with mean 0 and variance

$$\Sigma_{\nu} = \begin{bmatrix} \sigma_{1\nu}^2 & \rho_{\nu}\sigma_{1\nu}\sigma_{2\nu} \\ \rho_{\nu}\sigma_{1\nu}\sigma_{2\nu} & \sigma_{2\nu}^2 \end{bmatrix}$$

The observation-level errors $\epsilon_{1it}$ and $\epsilon_{2it}$ are independent of the random effects and are also bivariate normal, with mean 0 and variance

$$\Sigma = \begin{bmatrix} \sigma_{1}^2 & \rho\sigma_{1} \\ \rho\sigma_{1} & 1 \end{bmatrix}$$

When we condition on the random effects $\nu_{1i}$ and $\nu_{2i}$, we can write the joint density of the $y_{it}$ and $s_{it}$ using the conditional density of the selection error $\epsilon_{2it}$ on the outcome error $\epsilon_{1it}$.

For the selection indicator $s_{it}$, we have lower limit $l_{it}$ and upper limit $u_{it}$,

$$l_{it} = \begin{cases} -\infty & s_{it} = 0 \\ -z_{it}\alpha - \nu_{2i} - \frac{\rho}{\sigma_{1}} (y_{it} - x_{it}\beta - \nu_{1i}) & s_{it} = 1 \end{cases}$$

$$u_{it} = \begin{cases} -z_{it}\alpha - \nu_{2i} & s_{it} = 0 \\ \infty & s_{it} = 1 \end{cases}$$

Then, the joint density of $y_{it}$ and $s_{it}$ conditional on the random effects is

$$f(y_{it}, s_{it} | \nu_{1i}, \nu_{2i}) = \begin{cases} \Phi \left( \frac{-l_{it}}{\sqrt{1-\rho^2}} \right) + \phi \left( \frac{y_{it} - x_{it}\beta}{\sigma_{1}} \right) & s_{it} = 1 \\ \Phi \left( \frac{u_{it}}{\sqrt{1-\rho^2}} \right) & s_{it} = 0 \end{cases}$$
Note that each panel has the same random effects for each observation. So the likelihood for panel \( i \) is

\[
L_i = \int_{\mathbb{R}^2} \left[ \prod_{t=1}^{N_i} f(y_{it}, s_{it} | \nu_{1i}, \nu_{2i}) \phi_2((\nu_{1i}, \nu_{2i}), \Sigma_{\nu}) \right] d\nu_{1i} d\nu_{2i} 
\]

(1)

This multivariate integral is generally not tractable. We can use a change-of-variables technique to transform it into a set of nested univariate integrals. Let \( L \) be the Cholesky decomposition of \( \Sigma_{\nu} \); that is, \( \Sigma_{\nu} = LL' \). It follows that \( (\nu_{1i}, \nu_{2i})' = L\psi_i \), where \( \psi_i \) is a vector of independent standard normal random variables.

We can rewrite (1) as

\[
L_i = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \left\{ \prod_{t=1}^{N_i} f(y_{it}, s_{it} | (\nu_{1i}, \nu_{2i})' = L\psi_i) \right\} \phi(\psi_{1i}) \phi(\psi_{2i}) d\psi_{1i} d\psi_{2i}
\]

Now the univariate integral can be approximated using Gauss–Hermite quadrature (GHQ). For \( q \)-point GHQ, let the abscissa and weight pairs be denoted by \( (a^*_k, w^*_k) \), where \( k = 1, \ldots, q \). The GHQ approximation is then

\[
\int_{-\infty}^{\infty} f(x) \exp(-x^2) dx \approx \sum_{k=1}^{q} w^*_k f(a^*_k)
\]

Consider a 2-dimensional quadrature grid containing \( q \) quadrature points in both dimensions. Let the vector of abscissas \( a_k = (a_{k1}, a_{k2})' \) be a point in this grid, and let \( w_k = (w_{k1}, w_{k2})' \) be the vector of corresponding weights.

The GHQ approximation to the likelihood for a given panel is

\[
L_i = \sum_{k_1=1}^{q} \sum_{k_2=1}^{q} \left\{ \prod_{t=1}^{N_i} f(y_{it}, s_{it} | (\nu_{1i}, \nu_{2i})' = La_k) \right\} \left\{ \prod_{s=1}^{2} w_{ks} \right\}
\]

Rather than using regular GHQ, we can use mean–variance adaptive GHQ. Fixing the observed variables and model parameters in the integrand of (1), we see the posterior density for \( \psi_i \) is proportional to

\[
\left\{ \prod_{t=1}^{N_i} f(y_{it}, s_{it} | (\nu_{1i}, \nu_{2i})' = L\psi_i) \right\} \phi(\psi_i)
\]

It is reasonable to assume that this posterior density can be approximated by a multivariate normal density with mean vector \( \mu_{\psi_i} \) and variance matrix \( \tau_{\psi_i} \). Instead of using the prior density of \( \psi_i \) as the weighting distribution in the integral, we can use our approximation for the posterior density,

\[
L_i = \int_{\mathbb{R}^2} \left\{ \prod_{t=1}^{N_i} f(y_{it}, s_{it} | (\nu_{1i}, \nu_{2i})' = L\psi_i) \right\} \phi(\psi_i) \phi(\psi_i, \mu_{\psi_i}, \tau_{\psi_i}) d\psi_i
\]
The likelihood is then approximated by

\[ L_i = \sum_{k_1=1}^{q} \ldots \sum_{k_2=1}^{q} \left\{ \prod_{t=1}^{N_i} f(y_{it}, s_{it} | (\nu_{1i}, \nu_{2i})' = L\alpha_k) \right\} \left\{ 2 \prod_{s=1}^{\omega_{ks}} \right\} \]

where \( \alpha_k \) and \( \omega_{ks} \) are the adaptive versions of the abscissas and weights after an orthogonalizing transformation, which eliminates posterior covariances between elements of \( \psi_i \). The posterior means \( \mu_{vi} \) and posterior variances \( \tau_{vi} \) are computed iteratively by updating the posterior moments by using the mean–variance adaptive GHQ approximation, starting with a 0 mean vector and identity variance matrix.

The log likelihood for all panels is then

\[ \ln L = \sum_{i=1}^{N} \left( \ln \sum_{k_1=1}^{q} \ldots \sum_{k_2=1}^{q} \left\{ \prod_{t=1}^{N_i} f(y_{it}, s_{it} | (\nu_{1i}, \nu_{2i})' = L\alpha_k) \right\} \left\{ 2 \prod_{s=1}^{\omega_{ks}} \right\} \right) \]

The conditional mean of \( y_{it} \) is

\[ E(y_{it} | x_{it}) = x_{it}\beta \]

\texttt{xtheckman} results are obtained using \texttt{xtregress}; see Methods and formulas of [ERM] \texttt{egress}.

References


Heckman, J. 1976. The common structure of statistical models of truncation, sample selection and limited dependent variables and a simple estimator for such models. \textit{Annals of Economic and Social Measurement} 5: 475–492.


Also see

[XT] xtheckman postestimation — Postestimation tools for xtheckman
[XT] xteregress — Extended random-effects linear regression
[XT] xtreg — Fixed-, between-, and random-effects and population-averaged linear models
[XT] xtset — Declare data to be panel data
[ERM] eregress — Extended linear regression
[R] heckman — Heckman selection model
[R] regress — Linear regression
[U] 20 Estimation and postestimation commands