> **xtologit** — Random-effects ordered logistic models

Description

xtologit fits random-effects ordered logistic models. The actual values taken on by the dependent variable are irrelevant, although larger values are assumed to correspond to "higher" outcomes. The conditional distribution of the dependent variable given the random effects is assumed to be multinomial with success probability determined by the logistic cumulative distribution function.

Quick start

Random-effects ordered logistic model of y as a function of x using xtset data

    xtologit y x

Add indicators for levels of categorical variable a

    xtologit y x i.a

Same as above, but report odds ratios

    xtologit y x i.a, or

With cluster–robust standard errors for panels nested within cvar

    xtologit y x i.a, vce(cluster cvar)

Menu

Statistics > Longitudinal/panel data > Ordinal outcomes > Logistic regression (RE)

Syntax

> xtologit *depvar* [*indepvars*] [*[if](if)*] [*[in](in)*] [*weight*] [, *options*]

options	Description
Model	
<u>off</u>set(*varname*)	include *varname* in model with coefficient constrained to 1
<u>constr</u>aints(*constraints*)	apply specified linear constraints
SE/Robust	
vce(*vcetype*)	*vcetype* may be oim, <u>r</u>obust, <u>cl</u>uster *clustvar*, <u>boot</u>strap, or <u>jack</u>knife
Reporting	
<u>l</u>evel(*#*)	set confidence level; default is level(95)
or	report odds ratios
lrmodel	perform the likelihood-ratio model test instead of the default Wald test
nocnsreport	do not display constraints
display_options	control columns and column formats, row spacing, line width, display of omitted variables and base and empty cells, and factor-variable labeling
Integration	
<u>intm</u>ethod(*intmethod*)	integration method; *intmethod* may be <u>mvaghermite</u> (the default) or <u>ghermite</u>
<u>intp</u>oints(*#*)	use *#* quadrature points; default is intpoints(12)
Maximization	
maximize_options	control the maximization process; seldom used
<u>startg</u>rid(*numlist*)	improve starting value of the random-intercept parameter by performing a grid search
nodisplay	suppress display of header and coefficients
collinear	keep collinear variables
coeflegend	display legend instead of statistics

A panel variable must be specified; see [XT] **xtset**.

indepvars may contain factor variables; see [U] **11.4.3 Factor variables**.

depvar and *indepvars* may contain time-series operators; see [U] **11.4.4 Time-series varlists**.

bayes, by, collect, fp, and statsby are allowed; see [U] **11.1.10 Prefix commands**. For more details, see [BAYES] **bayes: xtologit**.

fweights, iweights, and pweights are allowed; see [U] **11.1.6 weight**.

startgrid(), nodisplay, collinear, and coeflegend do not appear in the dialog box.

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

Options

Model

offset(*varname*), constraints(*constraints*); see [R] **Estimation options**.

SE/Robust

vce(*vcetype*) specifies the type of standard error reported, which includes types that are derived from asymptotic theory (oim), that are robust to some kinds of misspecification (robust), that allow for intragroup correlation (cluster *clustvar*), and that use bootstrap or jackknife methods (bootstrap, jackknife); see [XT] *vce_options*.

Specifying vce(robust) is equivalent to specifying vce(cluster *panelvar*); see *xtologit and the robust VCE estimator* in *Methods and formulas*.

Reporting

level(*#*); see [R] **Estimation options**.

or reports the estimated coefficients transformed to odds ratios, that is, e^b rather than b. Standard errors and confidence intervals are similarly transformed. This option affects how results are displayed, not how they are estimated. or may be specified at estimation or when replaying previously estimated results.

lrmodel, nocnsreport; see [R] **Estimation options**.

display_options: noci, nopvalues, noomitted, vsquish, noemptycells, baselevels, allbaselevels, nofvlabel, fvwrap(*#*), fvwrapon(*style*), cformat(%*fmt*), pformat(%*fmt*), sformat(%*fmt*), and nolstretch; see [R] **Estimation options**.

Integration

intmethod(*intmethod*), intpoints(*#*); see [R] **Estimation options**.

Maximization

maximize_options: difficult, technique(*algorithm_spec*), iterate(*#*), [no]log, trace, gradient, showstep, hessian, showtolerance, tolerance(*#*), ltolerance(*#*), nrtolerance(*#*), nonrtolerance, and from(*init_specs*); see [R] **Maximize**. These options are seldom used.

The following options are available with xtologit but are not shown in the dialog box:

startgrid(*numlist*) performs a grid search to improve the starting value of the random-intercept parameter. No grid search is performed by default unless the starting value is found to not be feasible; in this case, xtologit runs startgrid(0.1 1 10) and chooses the value that works best. You may already be using a default form of startgrid() without knowing it. If you see xtologit displaying Grid node 1, Grid node 2, ... following Grid node 0 in the iteration log, that is xtologit doing a default search because the original starting value was not feasible.

nodisplay is for programmers. It suppresses the display of the header and the coefficients.

collinear, coeflegend; see [R] **Estimation options**.

Remarks and examples

Remarks are presented under the following heading:

> Overview
> Video example

Overview

xtologit fits random-effects ordered logistic models. Ordered logistic models are used to estimate relationships between an ordinal dependent variable and a set of independent variables. An *ordinal* variable is a variable that is categorical and ordered, for instance, "poor", "good", and "excellent", which might indicate a person's current health status or the repair record of a car. If there are only two outcomes, see [XT] **xtlogit**, [XT] **xtprobit**, and [XT] **xtcloglog**. This entry is concerned only with more than two outcomes.

▷ Example 1

We use the data from the "Television, School, and Family Smoking Prevention and Cessation Project" (Flay et al. 1988; Rabe-Hesketh and Skrondal 2022, chap. 11), where schools were randomly assigned into one of four groups defined by two treatment variables. Students within each school are nested in classes, and classes are nested in schools. In this example, we ignore the variability of classes within schools; see example 2 of [ME] **meologit** for a model that incorporates the additional class-level variance component. The dependent variable is the tobacco and health knowledge score (thk) collapsed into four ordered categories. We regress the outcome on the treatment variables and their interaction and control for the pretreatment score.

```
. use https://www.stata-press.com/data/r18/tvsfpors
(Television, School, and Family Project)

. xtset school

Panel variable: school (unbalanced)

. xtologit thk prethk cc##tv

Fitting comparison model:

Iteration 0:  Log likelihood =  -2212.775
Iteration 1:  Log likelihood =  -2125.509
Iteration 2:  Log likelihood = -2125.1034
Iteration 3:  Log likelihood = -2125.1032

Refining starting values:

Grid node 0:  Log likelihood = -2136.2426

Fitting full model:

Iteration 0:  Log likelihood = -2136.2426  (not concave)
Iteration 1:  Log likelihood = -2120.2577
Iteration 2:  Log likelihood = -2119.7574
Iteration 3:  Log likelihood = -2119.7428
Iteration 4:  Log likelihood = -2119.7428
```

Random-effects ordered logistic regression   Number of obs   =   1,600
Group variable: school   Number of groups =   28

Random effects u_i ~ Gaussian   Obs per group:
                                                              min =   18
                                                              avg =   57.1
                                                              max =   137

Integration method: mvaghermite   Integration pts. =   12

                                                  Wald chi2(4)   = 128.06
Log likelihood = -2119.7428   Prob > chi2   = 0.0000

thk	Coefficient	Std. err.	z	P>|z|	[95% conf. interval]	
prethk	.4032892	.03886	10.38	0.000	.327125	.4794534
1.cc	.9237904	.204074	4.53	0.000	.5238127	1.323768
1.tv	.2749937	.1977424	1.39	0.164	−.1125744	.6625618
cc#tv						
1 1	−.4659256	.2845963	−1.64	0.102	−1.023724	.0918728
/cut1	−.0884493	.1641062			−.4100916	.233193
/cut2	1.153364	.165616			.8287625	1.477965
/cut3	2.33195	.1734199			1.992053	2.671846
/sigma2_u	.0735112	.0383106			.0264695	.2041551

LR test vs. ologit model: chibar2(01) = 10.72   Prob >= chibar2 = 0.0005

The estimation table reports the parameter estimates, the estimated cutpoints $(\kappa_1, \kappa_2, \kappa_3)$, and the estimated panel-level variance component labeled sigma2_u. The parameter estimates can be interpreted just as the output from a standard ordered logistic regression would be interpreted; see [R] **ologit**. For example, we find that students with higher preintervention scores tend to have higher postintervention scores.

Underneath the parameter estimates and the cutpoints, the table shows the estimated variance component. The estimate of σ_u^2 is 0.074 with standard error 0.038. The reported likelihood-ratio test shows that there is enough variability between schools to favor a random-effects ordered logistic regression over a standard ordered logistic regression.

◁

❑ Technical note

The random-effects model is calculated using quadrature, which is an approximation whose accuracy depends partially on the number of integration points used. We can use the quadchk command to see if changing the number of integration points affects the results. If the results change, the quadrature approximation is not accurate given the number of integration points. Try increasing the number of integration points using the intpoints() option and run quadchk again. Do not attempt to interpret the results of estimates when the coefficients reported by quadchk differ substantially. See [XT] **quadchk** for details and [XT] **xtprobit** for an example.

Because the xtologit likelihood function is calculated by Gauss–Hermite quadrature, on large problems the computations can be slow. Computation time is roughly proportional to the number of points used for the quadrature.

❑

Video example

Ordered logistic and probit for panel data

Stored results

xtologit stores the following in e():

Scalars
e(N)	number of observations
e(N_g)	number of groups
e(k)	number of parameters
e(k_aux)	number of auxiliary parameters
e(k_eq)	number of equations in e(b)
e(k_eq_model)	number of equations in overall model test
e(k_dv)	number of dependent variables
e(k_cat)	number of categories
e(df_m)	model degrees of freedom
e(ll)	log likelihood
e(ll_0)	log likelihood, constant-only model
e(ll_c)	log likelihood, comparison model
e(chi2)	χ^2
e(chi2_c)	χ^2 for comparison test
e(N_clust)	number of clusters
e(sigma_u)	panel-level standard deviation
e(n_quad)	number of quadrature points
e(g_min)	smallest group size
e(g_avg)	average group size
e(g_max)	largest group size
e(p)	p-value for model test
e(rank)	rank of e(V)
e(rank0)	rank of e(V) for constant-only model
e(ic)	number of iterations
e(rc)	return code
e(converged)	1 if converged, 0 otherwise

Macros
e(cmd)	meglm
e(cmd2)	xtologit
e(cmdline)	command as typed
e(depvar)	name of dependent variable
e(covariates)	list of covariates
e(ivar)	variable denoting groups

e(wtype)	weight type
e(wexp)	weight expression
e(title)	title in estimation output
e(clustvar)	name of cluster variable
e(offset)	linear offset variable
e(chi2type)	Wald or LR; type of model χ^2 test
e(vce)	*vcetype* specified in vce()
e(vcetype)	title used to label Std. err.
e(intmethod)	integration method
e(distrib)	Gaussian; the distribution of the random effect
e(opt)	type of optimization
e(which)	max or min; whether optimizer is to perform maximization or minimization
e(ml_method)	type of ml method
e(user)	name of likelihood-evaluator program
e(technique)	maximization technique
e(properties)	b V
e(predict)	program used to implement predict
e(marginsok)	predictions allowed by margins
e(marginswtype)	weight type for margins
e(marginswexp)	weight expression for margins
e(marginsdefault)	default predict() specification for 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(ilog)	iteration log
e(gradient)	gradient vector
e(cat)	category values
e(V)	variance–covariance matrix of the estimators
e(V_modelbased)	model-based variance

Functions
e(sample)	marks estimation sample

In addition to the above, the following is stored in r():

Matrices
r(table)	matrix containing the coefficients with their standard errors, test statistics, p-values, and confidence intervals

Note that results stored in r() are updated when the command is replayed and will be replaced when any r-class command is run after the estimation command.

Methods and formulas

xtologit fits via maximum likelihood the random-effects model

$$\Pr(y_{it} > k | \boldsymbol{\kappa}, \mathbf{x}_{it}, \nu_i) = H(\mathbf{x}_{it}\boldsymbol{\beta} + \nu_i - \kappa_k)$$

for $i = 1, \ldots, n$ panels, where $t = 1, \ldots, n_i$, ν_i are independent and identically distributed $N(0, \sigma_\nu^2)$, and $\boldsymbol{\kappa}$ is a set of cutpoints $\kappa_1, \kappa_2, \ldots, \kappa_{K-1}$, where K is the number of possible outcomes; and $H(\cdot)$ is the logistic cumulative distribution function.

From the above, we can derive the probability of observing outcome k for response y_{it} as

$$
\begin{aligned}
p_{itk} \equiv \Pr(y_{it} = k | \boldsymbol{\kappa}, \mathbf{x}_{it}, \nu_i) &= \Pr(\kappa_{k-1} < \mathbf{x}_{it}\boldsymbol{\beta} + \nu_i + \epsilon_{it} \leq \kappa_k) \\
&= \Pr(\kappa_{k-1} - \mathbf{x}_{it}\boldsymbol{\beta} - \nu_i < \epsilon_{it} \leq \kappa_k - \mathbf{x}_{it}\boldsymbol{\beta} - \nu_i) \\
&= H(\kappa_k - \mathbf{x}_{it}\boldsymbol{\beta} - \nu_i) - H(\kappa_{k-1} - \mathbf{x}_{it}\boldsymbol{\beta} - \nu_i) \\
&= \frac{1}{1 + \exp(-\kappa_k + \mathbf{x}_{it}\boldsymbol{\beta} + \nu_i)} - \frac{1}{1 + \exp(-\kappa_{k-1} + \mathbf{x}_{it}\boldsymbol{\beta} + \nu_i)}
\end{aligned}
$$

where κ_0 is taken as $-\infty$ and κ_K is taken as $+\infty$. Here $\mathbf{x}_{it}$ does not contain a constant term, because its effect is absorbed into the cutpoints.

We may also express this model in terms of a latent linear response, where observed ordinal responses y_{it} are generated from the latent continuous responses, such that

$$
y_{it}^* = \mathbf{x}_{it}\boldsymbol{\beta} + \nu_i + \epsilon_{it}
$$

and

$$
y_{it} = \begin{cases}
1 & \text{if} & y_{it}^* \leq \kappa_1 \\
2 & \text{if} & \kappa_1 < y_{it}^* \leq \kappa_2 \\
\vdots & \\
K & \text{if} & \kappa_{K-1} < y_{it}^*
\end{cases}
$$

The errors ϵ_{it} are distributed as logistic with mean zero and variance $\pi^2/3$ and are independent of ν_i.

Given a set of panel-level random effects ν_i, we can define the conditional distribution for response y_{it} as

$$
\begin{aligned}
f(y_{it}, \boldsymbol{\kappa}, \mathbf{x}_{it}\boldsymbol{\beta} + \nu_i) &= \prod_{k=1}^{K} p_{itk}^{I_k(y_{it})} \\
&= \exp \sum_{k=1}^{K} \left\{ I_k(y_{it}) \log(p_{itk}) \right\}
\end{aligned}
$$

where

$$
I_k(y_{it}) = \begin{cases} 1 & \text{if } y_{it} = k \\ 0 & \text{otherwise} \end{cases}
$$

For panel i, $i = 1, \ldots, M$, the conditional distribution of $\mathbf{y}_i = (y_{i1}, \ldots, y_{in_i})'$ is

$$
\prod_{t=1}^{n_i} f(y_{it}, \boldsymbol{\kappa}, \mathbf{x}_{it}\boldsymbol{\beta} + \nu_i)
$$

and the panel-level likelihood l_i is given by

$$
\begin{aligned}
l_i(\boldsymbol{\beta}, \boldsymbol{\kappa}, \sigma_\nu^2) &= \int_{-\infty}^{\infty} \frac{e^{-\nu_i^2/2\sigma_\nu^2}}{\sqrt{2\pi}\sigma_\nu} \left\{ \prod_{t=1}^{n_i} f(y_{it}, \boldsymbol{\kappa}, \mathbf{x}_{it}\boldsymbol{\beta} + \nu_i) \right\} d\nu_i \\
&\equiv \int_{-\infty}^{\infty} g(y_{it}, \boldsymbol{\kappa}, x_{it}, \nu_i) d\nu_i
\end{aligned}
$$

This integral can be approximated with M-point Gauss–Hermite quadrature

$$\int_{-\infty}^{\infty} e^{-x^2} h(x)dx \approx \sum_{m=1}^{M} w_m^* h(a_m^*)$$

This is equivalent to

$$\int_{-\infty}^{\infty} f(x)dx \approx \sum_{m=1}^{M} w_m^* \exp\left\{(a_m^*)^2\right\} f(a_m^*)$$

where the w_m^* denote the quadrature weights and the a_m^* denote the quadrature abscissas. The log likelihood, L, is the sum of the logs of the panel-level likelihoods l_i.

The default approximation of the log likelihood is by mean–variance adaptive Gauss–Hermite quadrature, which approximates the panel-level likelihood with

$$l_i \approx \sqrt{2}\widehat{\sigma}_i \sum_{m=1}^{M} w_m^* \exp\left\{(a_m^*)^2\right\} g(y_{it}, \boldsymbol{\kappa}, x_{it}, \sqrt{2}\widehat{\sigma}_i a_m^* + \widehat{\mu}_i)$$

where $\widehat{\sigma}_i$ and $\widehat{\mu}_i$ are the adaptive parameters for panel i. The method of calculating the posterior mean and variance and using those parameters for $\widehat{\mu}_i$ and $\widehat{\sigma}_i$ is described in detail in Naylor and Smith (1982) and Skrondal and Rabe-Hesketh (2004). We start with $\widehat{\sigma}_{i,0} = 1$ and $\widehat{\mu}_{i,0} = 0$, and the posterior means and variances are updated in the jth iteration. That is, at the jth iteration of the optimization for l_i, we use

$$l_{i,j} \approx \sum_{m=1}^{M} \sqrt{2}\widehat{\sigma}_{i,j-1} w_m^* \exp\left\{(a_m^*)^2\right\} g(y_{it}, \boldsymbol{\kappa}, x_{it}, \sqrt{2}\widehat{\sigma}_{i,j-1} a_m^* + \widehat{\mu}_{i,j-1})$$

Letting

$$\tau_{i,m,j-1} = \sqrt{2}\widehat{\sigma}_{i,j-1} a_m^* + \widehat{\mu}_{i,j-1}$$

$$\widehat{\mu}_{i,j} = \sum_{m=1}^{M} (\tau_{i,m,j-1}) \frac{\sqrt{2}\widehat{\sigma}_{i,j-1} w_m^* \exp\left\{(a_m^*)^2\right\} g(y_{it}, \boldsymbol{\kappa}, x_{it}, \tau_{i,m,j-1})}{l_{i,j}}$$

and

$$\widehat{\sigma}_{i,j} = \sum_{m=1}^{M} (\tau_{i,m,j-1})^2 \frac{\sqrt{2}\widehat{\sigma}_{i,j-1} w_m^* \exp\left\{(a_m^*)^2\right\} g(y_{it}, \boldsymbol{\kappa}, x_{it}, \tau_{i,m,j-1})}{l_{i,j}} - (\widehat{\mu}_{i,j})^2$$

This is repeated until $\widehat{\mu}_{i,j}$ and $\widehat{\sigma}_{i,j}$ have converged for this iteration of the maximization algorithm. This adaptation is applied on every iteration.

The log likelihood can also be calculated by nonadaptive Gauss–Hermite quadrature with the option `intmethod(ghermite)`, where $\rho = \sigma_\nu^2/(\sigma_\nu^2 + 1)$:

$$L = \sum_{i=1}^{n} w_i \log\left\{ \Pr(y_{i1}, \ldots, y_{in_i} | \boldsymbol{\kappa}, \mathbf{x}_{i1}, \ldots, \mathbf{x}_{in_i}) \right\}$$

$$\approx \sum_{i=1}^{n} w_i \log\left[\frac{1}{\sqrt{\pi}} \sum_{m=1}^{M} w_m^* \prod_{t=1}^{n_i} f\left\{ y_{it}, \boldsymbol{\kappa}, \mathbf{x}_{it}\boldsymbol{\beta} + a_m^* \left(\frac{2\rho}{1-\rho}\right)^{1/2} \right\} \right]$$

Both quadrature formulas require that the integrated function be well approximated by a polynomial of degree equal to the number of quadrature points. The number of periods (panel size) can affect whether

$$\prod_{t=1}^{n_i} f(y_{it}, \boldsymbol{\kappa}, \mathbf{x}_{it}\boldsymbol{\beta} + \nu_i)$$

is well approximated by a polynomial. As panel size and ρ increase, the quadrature approximation can become less accurate. For large ρ, the random-effects model can also become unidentified. Adaptive quadrature gives better results for correlated data and large panels than nonadaptive quadrature; however, we recommend that you use the quadchk command (see [XT] **quadchk**) to verify the quadrature approximation used in this command, whichever approximation you choose.

xtologit and the robust VCE estimator

Specifying vce(robust) or vce(cluster *clustvar*) causes the Huber/White/sandwich VCE estimator to be calculated for the coefficients estimated in this regression. See [P] **_robust**, particularly *Introduction* and *Methods and formulas*. Wooldridge (2020) and Arellano (2003) discuss this application of the Huber/White/sandwich VCE estimator. As discussed by Wooldridge (2020), Stock and Watson (2008), and Arellano (2003), specifying vce(robust) is equivalent to specifying vce(cluster *panelvar*), where *panelvar* is the variable that identifies the panels.

Clustering on the panel variable produces a consistent VCE estimator when the disturbances are not identically distributed over the panels or there is serial correlation in ϵ_{it}.

The cluster–robust VCE estimator requires that there are many clusters and the disturbances are uncorrelated across the clusters. The panel variable must be nested within the cluster variable because of the within-panel correlation that is generally induced by the random-effects transform when there is heteroskedasticity or within-panel serial correlation in the idiosyncratic errors.

References

Allison, P. D. 2009. *Fixed Effects Regression Models*. Newbury Park, CA: Sage.

Arellano, M. 2003. *Panel Data Econometrics*. Oxford: Oxford University Press.

Baetschmann, G., A. Ballantyne, K. E. Staub, and R. Winkelmann. 2020. feologit: A new command for fitting fixed-effects ordered logit models. *Stata Journal* 20: 253–275.

Conway, M. R. 1990. A random effects model for binary data. *Biometrics* 46: 317–328. https://doi.org/10.2307/2531437.

Flay, B. R., B. R. Brannon, C. A. Johnson, W. B. Hansen, A. L. Ulene, D. A. Whitney-Saltiel, L. R. Gleason, S. Sussman, M. D. Gavin, K. M. Glowacz, D. F. Sobol, and D. C. Spiegel. 1988. The television, school, and family smoking cessation and prevention project: I. Theoretical basis and program development. *Preventive Medicine* 17: 585–607. https://doi.org/10.1016/0091-7435(88)90053-9.

Liang, K.-Y., and S. L. Zeger. 1986. Longitudinal data analysis using generalized linear models. *Biometrika* 73: 13–22. https://doi.org/10.1093/biomet/73.1.13.

Naylor, J. C., and A. F. M. Smith. 1982. Applications of a method for the efficient computation of posterior distributions. *Journal of the Royal Statistical Society, Series C* 31: 214–225. https://doi.org/10.2307/2347995.

Neuhaus, J. M. 1992. Statistical methods for longitudinal and clustered designs with binary responses. *Statistical Methods in Medical Research* 1: 249–273. https://doi.org/10.1177/096228029200100303.

Neuhaus, J. M., J. D. Kalbfleisch, and W. W. Hauck. 1991. A comparison of cluster-specific and population-averaged approaches for analyzing correlated binary data. *International Statistical Review* 59: 25–35. https://doi.org/10.2307/1403572.

Pendergast, J. F., S. J. Gange, M. A. Newton, M. J. Lindstrom, M. Palta, and M. R. Fisher. 1996. A survey of methods for analyzing clustered binary response data. *International Statistical Review* 64: 89–118. https://doi.org/10.2307/1403425.

Rabe-Hesketh, S., and A. Skrondal. 2022. *Multilevel and Longitudinal Modeling Using Stata*. 4th ed. College Station, TX: Stata Press.

Skrondal, A., and S. Rabe-Hesketh. 2004. *Generalized Latent Variable Modeling: Multilevel, Longitudinal, and Structural Equation Models*. Boca Raton, FL: Chapman and Hall/CRC.

Stock, J. H., and M. W. Watson. 2008. Heteroskedasticity-robust standard errors for fixed effects panel data regression. *Econometrica* 76: 155–174. https://doi.org/10.1111/j.0012-9682.2008.00821.x.

Twisk, J. W. R. 2013. *Applied Longitudinal Data Analysis for Epidemiology: A Practical Guide*. 2nd ed. Cambridge: Cambridge University Press.

Wooldridge, J. M. 2020. *Introductory Econometrics: A Modern Approach*. 7th ed. Boston: Cengage.

Also see

[XT] **xtologit postestimation** — Postestimation tools for xtologit

[XT] **quadchk** — Check sensitivity of quadrature approximation

[XT] **xtoprobit** — Random-effects ordered probit models

[XT] **xtset** — Declare data to be panel data

[BAYES] **bayes: xtologit** — Bayesian random-effects ordered logistic model

[ME] **meologit** — Multilevel mixed-effects ordered logistic regression

[R] **logistic** — Logistic regression, reporting odds ratios

[R] **logit** — Logistic regression, reporting coefficients

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