

xtstreg — Random-effects parametric survival models

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Description

`xtstreg` fits random-effects parametric survival-time models. The conditional distribution of the response given the random effects is assumed to be an exponential, a Weibull, a lognormal, a loglogistic, or a gamma distribution. `xtstreg` can be used with single- or multiple-record `st` data.

Quick start

Declare `pvar` as the panel variable using `xtset`, and declare data to be survival-time data using `stset`

```
xtset pvar
stset tvar, failure(fail)
```

Random-effects Weibull survival model with covariates `x1` and `x2`

```
xtstreg x1 x2, distribution(weibull)
```

Use accelerated failure-time metric instead of proportional-hazards metric

```
xtstreg x1 x2, distribution(weibull) time
```

As above, but with panel-level probability weights `wvar`

```
xtstreg x1 x2 [pw=wvar], distribution(weibull) time
```

Random-effects model with cluster-robust standard errors for panels nested within `cvar`

```
xtstreg x1 x2, distribution(weibull) vce(cluster cvar)
```

Menu

Statistics > Longitudinal/panel data > Parametric survival regression

Syntax

```
xtstreg [varlist] [if] [in] [weight], distribution(distname) [options]
```

<i>options</i>	Description
Model	
<u>noconstant</u>	suppress constant term
* <u>distribution</u> (<i>distname</i>)	specify survival distribution
<u>time</u>	use accelerated failure-time metric
<u>offset</u> (<i>varname</i>)	include <i>varname</i> in model with coefficient constrained to 1
<u>constraints</u> (<i>constraints</i>)	apply specified linear constraints
<u>collinear</u>	keep collinear variables
SE/Robust	
<u>vce</u> (<i>vcetype</i>)	<i>vcetype</i> may be <u>oim</u> , <u>robust</u> , <u>cluster</u> <i>clustvar</i> , <u>bootstrap</u> , or <u>jackknife</u>
Reporting	
<u>level</u> (#)	set confidence level; default is <u>level</u> (95)
<u>nohr</u>	do not report hazard ratios
<u>noshow</u>	do not show st setting information
<u>noskip</u>	perform overall model test as a likelihood-ratio test
<u>nocnsreport</u>	do not display constraints
<u>tratio</u>	report time ratios
<u>display_options</u>	control columns and column formats, row spacing, line width, display of omitted variables and base and empty cells, and factor-variable labeling
Integration	
<u>intmethod</u> (<i>intmethod</i>)	integration method; <i>intmethod</i> may be <u>mvaghermite</u> (the default) or <u>ghermite</u>
<u>intpoints</u> (#)	use # quadrature points; default is <u>intpoints</u> (12)
Maximization	
<u>maximize_options</u>	control the maximization process; seldom used
<u>startgrid</u> (<i>numlist</i>)	improve starting value of the random-intercept parameter by performing a grid search
<u>nodisplay</u>	suppress display of header and coefficients
<u>coeflegend</u>	display legend instead of statistics

*distribution(*distname*) is required.

<i>distname</i>	Description
<code>exponential</code>	exponential survival distribution
<code>loglogistic</code>	loglogistic survival distribution
<code>llogistic</code>	synonym for <code>loglogistic</code>
<code>weibull</code>	Weibull survival distribution
<code>lognormal</code>	lognormal survival distribution
<code>lnormal</code>	synonym for <code>lognormal</code>
<code>gamma</code>	gamma survival distribution

You must `stset` your data before using `xtstreg`; see [ST] [stset](#).

A panel variable must be specified. Use `xtset`; see [XT] [xtset](#).

`indepvars` may contain factor variables; see [U] [11.4.3 Factor variables](#).

`varlist` may contain time-series operators; see [U] [11.4.4 Time-series varlists](#).

`by`, `fp`, and `statsby` are allowed; see [U] [11.1.10 Prefix commands](#).

`fweights`, `iweights`, and `pweights` are allowed; see [U] [11.1.6 weight](#). Weights must be constant within panel.

`startgrid`, `nodisplay`, and `coeflegend` do not appear in the dialog box.

See [U] [20 Estimation and postestimation commands](#) for more capabilities of estimation commands.

Options

Model

`noconstant`; see [R] [estimation options](#).

`distribution(distname)` specifies the survival model to be fit. *distname* is one of the following: `exponential`, `loglogistic`, `llogistic`, `weibull`, `lognormal`, `lnormal`, or `gamma`. This option is required.

`time` specifies that the model be fit in the accelerated failure-time metric rather than in the log relative-hazard metric. This option is valid only for the exponential and Weibull models because these are the only models that have both a proportional-hazards and an accelerated failure-time parameterization. Regardless of metric, the likelihood function is the same, and models are equally appropriate in either metric; it is just a matter of changing interpretation.

`time` must be specified at estimation.

`offset(varname)` specifies that *varname* be included in the fixed-effects portion of the model with the coefficient constrained to be 1.

`constraints(constraints)`, `collinear`; 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 [xtstreg and the robust VCE estimator](#) in *Methods and formulas*.

Reporting

`level(#)`; see [R] [estimation options](#).

`nohr`, which may be specified at estimation or upon redisplaying results, specifies that coefficients rather than exponentiated coefficients be displayed, that is, that coefficients rather than hazard ratios be displayed. This option affects only how coefficients are displayed, not how they are estimated.

This option is valid only for the exponential and Weibull models because they have a natural proportional-hazards parameterization. These two models, by default, report hazard ratios (exponentiated coefficients).

`noshow` prevents `xtstreg` from showing the key `st` variables. This option is rarely used because most users type `stset`, `show` or `stset, noshow` to set once and for all whether they want to see these variables mentioned at the top of the output of every `st` command; see [ST] [stset](#).

`noskip`, `nocnsreport`; see [R] [estimation options](#).

`tratio` specifies that exponentiated coefficients, which are interpreted as time ratios, be displayed. `tratio` is appropriate only for the loglogistic, lognormal, and gamma models or for the exponential and Weibull models when fit in the accelerated failure-time metric.

`tratio` may be specified at estimation or upon replay.

display_options: `nocl`, `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 `xtstreg` 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 be not feasible, in which case `xtstreg` 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 `xtstreg` displaying Grid node 1, Grid node 2, . . . following Grid node 0 in the iteration log, that is `xtstreg` 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.

`coeflegend`; see [R] [estimation options](#).

Remarks and examples[stata.com](http://www.stata.com)

`xtstreg` fits random-effects parametric survival-time models. The following discussion relies on the jargon of survival analysis; if you are not familiar with survival-time data or time-to-event data, see [Introduction to survival analysis](#) in [ST] [survival analysis](#) for an overview of survival analysis in Stata and [ST] [Glossary](#) for a glossary of technical terms.

`xtstreg` is suitable only for data that have been `stset` as well as `xtset`. `stset` weights are not used; instead, weights must be specified at estimation. `xtstreg` requires “subjects”, as defined by option `id()` in `stset`, to be nested within panels identified by the `panelvar` specified in `xtset`. `xtstreg` can be used with multiple-record data, but it does not allow delayed entry or gaps.

For a Stata-specific introduction to survival analysis, see [Cleves, Gould, and Marchenko \(2016\)](#). [Rabe-Hesketh and Skrondal \(2012, chap. 14-15\)](#) is a good introductory read on applied longitudinal modeling of survival data.

▷ Example 1

In [example 11](#) of [\[ST\] streg](#), we fit a Weibull model with an inverse-Gaussian shared frailty to the recurrence times for catheter-insertion point infection for 38 kidney dialysis patients. In this example, the subjects are the catheter insertions, not the patients themselves. This is a function of how the data were recorded—the onset of risk occurs at the time the catheter is inserted and not, say, at the time of admission of the patient into the study. Thus we have two subjects (insertions) within each panel (patient). Each catheter insertion results in either infection (`infect==1`) or right-censoring (`infect==0`). Here we `stset` the data:

```
. use http://www.stata-press.com/data/r14/catheter
(Kidney data, McGilchrist and Aisbett, Biometrics, 1991)
. stset
-> stset time, failure(infect)
      failure event:  infect != 0 & infect < .
obs. time interval:  (0, time]
exit on or before:  failure
```

```
      76 total observations
      0 exclusions
```

```
      76 observations remaining, representing
      58 failures in single-record/single-failure data
      7424 total analysis time at risk and under observation
                at risk from t =          0
                earliest observed entry t =      0
                last observed exit t =        562
```

While it is reasonable to assume independence of patients, we would not want to assume that recurrence times within each patient are independent. The model used in [\[ST\] streg](#) allowed us to model the correlation by assuming that it was the result of a latent patient-level effect, or frailty.

Here we use `xtstreg` to fit a random-effects Weibull model with normally distributed random effects at the patient level. This is done by defining our panels as patients in the dataset.

```
. xtset patient
      panel variable:  patient (balanced)
. xtstreg age female, distribution(weibull)
      failure _d:  infect
      analysis time _t:  time

Fitting comparison model:
Iteration 0:  log likelihood = -1700758.8
Iteration 1:  log likelihood = -209.06397
Iteration 2:  log likelihood = -105.48579
Iteration 3:  log likelihood = -103.51354
Iteration 4:  log likelihood = -103.44376
Iteration 5:  log likelihood = -103.44362
Iteration 6:  log likelihood = -103.44362

Refining starting values:
Grid node 0:  log likelihood = -104.9032

Fitting full model:
Iteration 0:  log likelihood = -104.9032 (not concave)
Iteration 1:  log likelihood = -101.98184
Iteration 2:  log likelihood = -100.43558
Iteration 3:  log likelihood = -98.849674
Iteration 4:  log likelihood = -98.743848
Iteration 5:  log likelihood = -98.74355
Iteration 6:  log likelihood = -98.74355

Random-effects Weibull regression
Group variable:      patient

Number of obs      =      76
Number of groups   =      38
Obs per group:
      min =      2
      avg =     2.0
      max =      2

Integration method: mvaghermite
Integration pts.   =      12
Wald chi2(2)      =     10.17
Prob > chi2       =     0.0062

Log likelihood = -98.74355
```

_t	Haz. Ratio	Std. Err.	z	P> z	[95% Conf. Interval]	
age	1.007329	.0137828	0.53	0.594	.9806742	1.034708
female	.1910581	.0999004	-3.17	0.002	.0685629	.5324042
_cons	.0073346	.0072307	-4.99	0.000	.0010623	.0506427
/ln_p	.222825	.1386296	1.61	0.108	-.0488841	.494534
/sigma2_u	.8234584	.4812598			.2619194	2.588902

```
LR test vs. Weibull model:  chibar2(01) = 9.40          Prob >= chibar2 = 0.0011
```

The results are similar to those in [\[ST\] streg](#). The likelihood-ratio test compares the random-effects model with a survival model with fixed effects only. The results support the random-effects model.

For this model, `xtstreg` displays exponentiated coefficients, labeled as hazard ratios. These hazard ratios should be interpreted as “conditional hazard ratios”, that is, conditional on the random effects.

For example, the hazard ratio for `age` is 1.01. This means that according to the model, for a given patient, the hazard would increase 1% with each year of age. However, at the population level, marginal hazards corresponding to different levels of the covariates are not necessarily proportional; see [example 5](#) in [\[ME\] mestreg postestimation](#) for further discussion.

The exponentiated coefficients of covariates that usually remain constant within a panel do not have a natural interpretation as conditional hazard ratios. However, the magnitude of the exponentiated coefficients always gives an idea of the effect of the covariates. In this example, `female` is constant within the panel. The estimated hazard ratio for `female` is 0.19, which indicates that hazard functions for females tend to be smaller than hazard functions for males.

◀

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

□

Stored results

`xtstreg` stores the following in `e()`:

Scalars

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

Macros

<code>e(cmd)</code>	<code>gsem</code>
<code>e(cmd2)</code>	<code>xtstreg</code>
<code>e(cmdline)</code>	command as typed
<code>e(depvar)</code>	<code>_t</code>
<code>e(wtype)</code>	weight type

<code>e(wexp)</code>	weight expression (first-level weights)
<code>e(covariates)</code>	list of covariates
<code>e(ivar)</code>	variable denoting groups
<code>e(model)</code>	model name
<code>e(title)</code>	title in estimation output
<code>e(distribution)</code>	distribution
<code>e(clustvar)</code>	name of cluster variable
<code>e(offset)</code>	offset
<code>e(intmethod)</code>	integration method
<code>e(n_quad)</code>	number of integration points
<code>e(chi2type)</code>	Wald; type of model χ^2
<code>e(vce)</code>	<i>vcetype</i> specified in <code>vce()</code>
<code>e(vcetype)</code>	title used to label Std. Err.
<code>e(frm2)</code>	hazard or time
<code>e(opt)</code>	type of optimization
<code>e(which)</code>	max or min ; whether optimizer is to perform maximization or minimization
<code>e(ml_method)</code>	type of ml method
<code>e(user)</code>	name of likelihood-evaluator program
<code>e(technique)</code>	maximization technique
<code>e(properties)</code>	b V
<code>e(estat_cmd)</code>	program used to implement <code>estat</code>
<code>e(predict)</code>	program used to implement <code>predict</code>
<code>e(marginsok)</code>	predictions allowed by <code>margins</code>
<code>e(marginswexp)</code>	weight expression for <code>margins</code>
<code>e(asbalanced)</code>	factor variables <code>fvset</code> as <code>asbalanced</code>
<code>e(asobserved)</code>	factor variables <code>fvset</code> as <code>asobserved</code>

Matrices

<code>e(b)</code>	coefficient vector
<code>e(Cns)</code>	constraints matrix
<code>e(ilog)</code>	iteration log (up to 20 iterations)
<code>e(gradient)</code>	gradient vector
<code>e(V)</code>	variance–covariance matrix of the estimator
<code>e(V_modelbased)</code>	model-based variance

Functions

<code>e(sample)</code>	marks estimation sample
------------------------	-------------------------

Methods and formulas

Methods and formulas are presented under the following headings:

Survival models
xtstreg and the robust VCE estimator

Survival models

Survival models have a trivariate response (t_0, t, d) :

t_0 is the starting time under observation $t_0 \geq 0$;

t is the ending time under observation $t \geq t_0$; and

d is an indicator for failure $d \in \{0, 1\}$.

You must `stset` your data before using `xtstreg`; see [ST] `stset`. By `stsetting` your data, you define the variables `_t0`, `_t`, and `_d`, which serve as the trivariate response variable.

Let $i = 1, \dots, n$ panels, $j = 1, \dots, n_i$, and ν_{is} be unobservable panel-level random effects that are independent and identically distributed $N(0, \sigma_\nu^2)$.

Two often-used models for adjusting survivor functions for the effects of covariates are the accelerated failure-time (AFT) model and the multiplicative or proportional hazards (PH) model.

In the AFT model, the natural logarithm of the survival time, $\log t$, is expressed as a linear function of the covariates; when we incorporate the random effects, this yields the model

$$\log t_{ij} = \mathbf{x}_{ij}\boldsymbol{\beta} + \nu_i + \epsilon_{ij}$$

The $1 \times p$ row vector \mathbf{x}_{ij} contains the covariates for the fixed effects, with regression coefficients (fixed effects) $\boldsymbol{\beta}$.

The ϵ_{ij} are the observation-level errors with density $\varphi(\cdot)$. The distributional form of the error term determines the regression model. Five regression models are implemented in `xtstreg` using the AFT parameterization: exponential, gamma, loglogistic, lognormal, and Weibull. The lognormal regression model is obtained by letting $\varphi(\cdot)$ be the normal density. Similarly, by letting $\varphi(\cdot)$ be the logistic density, one obtains the loglogistic regression. Setting $\varphi(\cdot)$ equal to the extreme-value density yields the exponential and the Weibull regression models.

In the PH models fit by `xtstreg`, the covariates have a multiplicative effect on the hazard function

$$h(t_{ij}) = h_0(t_{ij}) \exp(\mathbf{x}_{ij}\boldsymbol{\beta} + \nu_i)$$

for some baseline hazard function $h_0(t)$. For the `xtstreg` command, $h_0(t)$ is assumed to be parametric. The exponential and Weibull models are implemented in `xtstreg` for the PH parameterization. These two models are implemented using both the AFT and PH parameterizations.

The survivor function for a given family is the complement of the cumulative distribution function, $S(t) = 1 - F(t)$. The density for a failure at time t is given by

$$g(t) = \frac{\partial F(t)}{\partial t} = -\frac{\partial S(t)}{\partial t}$$

Some distributions contain ancillary parameters that are not denoted here.

The conditional density for a failure at time t is

$$g(t|t \geq t_0, d = 1) = g(t)/S(t_0)$$

and the conditional probability of survival without failure up to time t is

$$P(T \geq t|t \geq t_0, d = 0) = S(t)/S(t_0)$$

The conditional likelihood is given by

$$L(t_0, t, d) = \left\{ \frac{g(t)}{S(t_0)} \right\}^d \left\{ \frac{S(t)}{S(t_0)} \right\}^{1-d}$$

See *Survival distributions* in [SEM] [methods and formulas for gsem](#) for the specific density function corresponding to each distribution.

Given the panel-level random effect ν_i , the conditional distribution of $\mathbf{t}_i = (t_{i1}, \dots, t_{in_i})'$ given $\boldsymbol{\eta}_i = (\mathbf{x}_{i1}\boldsymbol{\beta} + \nu_i, \dots, \mathbf{x}_{in_i}\boldsymbol{\beta} + \nu_i)$ for panel i is

$$f(\mathbf{t}_i|\boldsymbol{\eta}_i) = \prod_{j=1}^{n_i} f(t_{ij}|\eta_{ij})$$

where $f(t_{ij}|\eta_{ij})$ is the contribution to the likelihood from observation ij ; that is,

$$f(t_{ij}|\eta_{ij}) = \left\{ \frac{g(t_{ij}|\mathbf{x}_{ij}\boldsymbol{\beta} + \nu_i)}{S(t_{0ij}|\mathbf{x}_{ij}\boldsymbol{\beta} + \nu_i)} \right\}^{d_{ij}} \left\{ \frac{S(t_{ij}|\mathbf{x}_{ij}\boldsymbol{\beta} + \nu_i)}{S(t_{0ij}|\mathbf{x}_{ij}\boldsymbol{\beta} + \nu_i)} \right\}^{1-d_{ij}}$$

where $g(t|\eta)$ and $S(t|\eta)$ are, respectively, the density and the survivor function conditional on the linear prediction η .

As mentioned above, `xtstreg` does not allow delayed entry or gaps. Therefore, the first observation for a given subject will have a value of $t_0 = 0$, and subsequent spells for the subject must start at the end of the previous spell. That is, if observations ij and $i, j + 1$ belong to the same subject, then $t_{0i,j+1} = t_{ij}$.

Given a normal distribution $N(0, \sigma_\nu^2)$ for the random effect ν_i , the panel-level likelihood \mathcal{L}_i is given by

$$\mathcal{L}_i(\boldsymbol{\beta}, \sigma_\nu) = \int_{-\infty}^{\infty} \frac{e^{-\nu_i^2/2\sigma_\nu^2}}{\sqrt{2\pi}\sigma_\nu} \left\{ \prod_{j=1}^{n_i} f(t_{ij}|\mathbf{x}_{ij}\boldsymbol{\beta} + \nu_i) \right\} d\nu_i \quad (1)$$

The integration in (1) has no closed form and thus must be approximated. `xtstreg` offers two approximation methods: mean–variance adaptive Gauss–Hermite quadrature (default) and nonadaptive Gauss–Hermite quadrature. For details on these integration methods, see [\[SEM\] methods and formulas for gsem](#). To see how panel-level weights are incorporated into the likelihood function, see [Survey data in \[SEM\] methods and formulas for gsem](#).

The log likelihood for the entire dataset is simply the sum of the contributions of the n individual panels; namely, $\mathcal{L}(\boldsymbol{\beta}, \sigma_\nu) = \sum_{i=1}^n \mathcal{L}_i(\boldsymbol{\beta}, \sigma_\nu)$.

Maximization of $\mathcal{L}(\boldsymbol{\beta}, \sigma_\nu)$ is performed with respect to $(\boldsymbol{\beta}, \sigma_\nu^2)$. Parameter estimates are stored in `e(b)` as $(\hat{\boldsymbol{\beta}}, \hat{\sigma}_\nu^2)$, with the corresponding variance–covariance matrix stored in `e(V)`.

xtstreg 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 \(2016\)](#) and [Arellano \(2003\)](#) discuss this application of the Huber/White/sandwich VCE estimator. As discussed by [Wooldridge \(2016\)](#), [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 be many clusters and that the disturbances be 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

- Arellano, M. 2003. *Panel Data Econometrics*. Oxford: Oxford University Press.
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- Wooldridge, J. M. 2016. *Introductory Econometrics: A Modern Approach*. 6th ed. Boston: Cengage.

Also see

- [XT] [xtstreg postestimation](#) — Postestimation tools for xtstreg
- [XT] [quadchk](#) — Check sensitivity of quadrature approximation
- [XT] [xtset](#) — Declare data to be panel data
- [ME] [mestreg](#) — Multilevel mixed-effects parametric survival models
- [ST] [streg](#) — Parametric survival models
- [ST] [stset](#) — Declare data to be survival-time data
- [U] [20 Estimation and postestimation commands](#)