xtstreg — Random-effects parametric survival models

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

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

Random-effects Weibull survival model with covariates x1 and x2

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

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

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

As above, but with panel-level probability weights wvar

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

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

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

Menu

Statistics > Longitudinal/panel data > Survival models > Parametric survival models (RE)
Syntax

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

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*`distribution(distname)` is required.
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<td>gamma survival distribution</td>
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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`, `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**

`noconstant`; see `[R] Estimation options`.

`distribution(distname)` specifies the survival model to be fit. `distname` is one of the following: `exponential`, `loglogistic`, `logistic`, `weibull`, `lognormal`, `normal`, 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)`; 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(#) for [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 hazards 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.

lrmodel, 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: 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 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. collinear, coeflegend; see [R] Estimation options.

Remarks and examples

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 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 https://www.stata-press.com/data/r16/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
    7,424  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 \texttt{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.

\begin{verbatim}
. xtset patient
  panel variable: patient (balanced)
. xtstreg age female, distribution(weibull)
  failure _d: infect
  analysis time _t: time
\end{verbatim}

Fitting comparison model:

\begin{verbatim}
Iteration 0:  log likelihood = -1700989.9
Iteration 1:  log likelihood = -440.1998
Iteration 2:  log likelihood = -336.62162
Iteration 3:  log likelihood = -334.64937
Iteration 4:  log likelihood = -334.57959
Iteration 5:  log likelihood = -334.57944
Iteration 6:  log likelihood = -334.57944
\end{verbatim}

Refining starting values:

\begin{verbatim}
Grid node 0:  log likelihood = -336.03903
\end{verbatim}

Fitting full model:

\begin{verbatim}
Iteration 0:  log likelihood = -336.03903  (not concave)
Iteration 1:  log likelihood = -333.12188
Iteration 2:  log likelihood = -330.38629
Iteration 3:  log likelihood = -329.89525
Iteration 4:  log likelihood = -329.87946
Iteration 5:  log likelihood = -329.87938
Iteration 6:  log likelihood = -329.87938
\end{verbatim}

\begin{verbatim}
Random-effects Weibull PH 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
Log likelihood = -329.87938  Prob > chi2 = 0.0062
\end{verbatim}

\begin{verbatim}
|    _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  | -4.49 | 0.000| .0010623 .0506427  |
| _cons   | .0073346   | .0072307  | -4.99 | 0.000| .0010623 .0506427  |
| /ln_p   | .222825    | .1386296  | -4.49 | 0.000| .0010623 .0506427  |
| /sigma_u| .8234583   | .4812598  | -4.49 | 0.000| .0010623 .0506427  |
\end{verbatim}

Note: Estimates are transformed only in the first equation.
Note: \_cons estimates baseline hazard (conditional on zero random effects).
LR test vs. Weibull model: chibar2(01) = 9.40  Prob >= chibar2 = 0.0011

The results are similar to those in \texttt{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, \texttt{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 \texttt{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

- e(N) number of observations
- e(N_g) number of groups
- 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_dv) number of dependent variables
- e(df_m) model degrees of freedom
- e(ll) log likelihood
- e(N_clust) number of clusters
- e(ch12) χ²
- e(p) p-value for model test
- e(ll_c) log likelihood, comparison model
- e(ch12_c) χ², comparison model
- 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(rank) rank of e(V)
- e(ic) number of iterations
- e(rc) return code
- e(converged) 1 if converged, 0 otherwise

Macros

- e(cmd) gsem
- e(cmd2) xtstreg
- e(cmdline) command as typed
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 \( i = 1, \ldots, n \) panels, \( j = 1, \ldots, n_i \), and \( \nu_i \)'s be unobservable panel-level random effects that are independent and identically distributed \( N(0, \sigma^2_\nu) \).

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

\[
\log t_{ij} = x_{ij} \beta + \nu_i + \epsilon_{ij}
\]

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

The \( \epsilon_{ij} \) 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 \texttt{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 \texttt{xtstreg}, the covariates have a multiplicative effect on the hazard function

\[
h(t_{ij}) = h_0(t_{ij}) \exp(x_{ij} \beta + \nu_i)
\]
for some baseline hazard function \( h_0(t) \). For the \texttt{xtstreg} command, \( h_0(t) \) is assumed to be parametric. The exponential and Weibull models are implemented in \texttt{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 \textit{Survival distributions} in [SEM] \textit{Methods and formulas for gsem} for the specific density function corresponding to each distribution.
Given the panel-level random effect \( \nu_i \), the conditional distribution of \( t_i = (t_{i1}, \ldots, t_{in_i})' \) given \( \eta_i = (x_{i1}\beta + \nu_i, \ldots, x_{in_i}\beta + \nu_i) \) for panel \( i \) is
\[
f(t_i | \eta_i) = \prod_{j=1}^{n_i} f(t_{ij} | \eta_{ij})
\]
where \( f(t_{ij} | \eta_{ij}) \) is the contribution to the likelihood from observation \( ij \); that is,
\[
f(t_{ij} | \eta_{ij}) = \begin{cases} g(t_{ij} | x_{ij}\beta + \nu_i) & d_{ij} \\ S(t_{0ij} | x_{ij}\beta + \nu_i) & S(t_{0ij} | x_{ij}\beta + \nu_i) \end{cases}^{1-d_{ij}}
\]
where \( g(t | \eta) \) and \( S(t | \eta) \) are, respectively, the density and the survivor function conditional on the linear prediction \( \eta \).

As mentioned above, \texttt{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 \( N(0, \sigma^2_\nu) \) for the random effect \( \nu_i \), the panel-level likelihood \( L_i \) is given by
\[
L_i(\beta, \sigma_\nu) = \int_{-\infty}^{\infty} \frac{e^{-\nu_i^2/2\sigma^2_\nu}}{\sqrt{2\pi}\sigma_\nu} \left\{ \prod_{j=1}^{n_i} f(t_{ij} | x_{ij}\beta + \nu_i) \right\} d\nu_i
\]  \hspace{1cm} (1)

The integration in (1) has no closed form and thus must be approximated. \texttt{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 \texttt{gsem}. To see how panel-level weights are incorporated into the likelihood function, see Survey data in [SEM] Methods and formulas for \texttt{gsem}.

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

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

**xtstreg and the robust VCE estimator**

Specifying \texttt{vce(robust)} or \texttt{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 \texttt{vce(robust)} is equivalent to specifying \texttt{vce(cluster panelvar)}, where \texttt{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 \( \epsilon_{it} \).

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


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