

stset — Declare data to be survival-time data

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Description

`st` refers to survival-time data, which are fully described below.

`stset` declares the data in memory to be `st` data, informing Stata of key variables and their roles in a survival-time analysis. When you `stset` your data, `stset` runs various data consistency checks to ensure that what you have declared makes sense. If the data are weighted, you specify the weights when you `stset` the data, not when you issue the individual `st` commands.

`streset` changes how the `st` dataset is declared. In multiple-record data, `streset` can also temporarily set the sample to include records from before the time at risk (called the past) and records after failure (called the future). Then typing `streset` without arguments resets the sample back to the analysis sample.

`st` displays how the dataset is currently declared.

Whenever you type `stset` or `streset`, Stata runs or reruns data consistency checks to ensure that what you are now declaring (or declared in the past) makes sense. Thus if you have made any changes to your data or simply wish to verify how things are, you can type `streset` with no options.

`stset`, `clear` is for use by programmers. It causes Stata to forget the `st` markers, making the data no longer `st` data to Stata. The data remain unchanged. It is not necessary to `stset`, `clear` before doing another `stset`.

Quick start

Single-record-per-subject survival data

Specify time of failure, recorded in `tvar`, for data without censoring

```
stset tvar
```

Specify time of censoring or failure, `tvar`, and specify that `event = 2` represents a failure

```
stset tvar, failure(event==2)
```

Specify that `event = 2` and `event = 3` represent failures

```
stset tvar, failure(event==2 3)
```

Specify failure using indicator variable `fail`

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

Same as above, and specify that subjects become at risk at time `torig`

```
stset tvar, failure(fail) origin(time torig)
```

Specify that subjects become at risk at time 0, but enter the study at time `tenter`

```
stset tvar, fail(failure) enter(time tenter)
```

Specify subjects become at risk at time `torig`, and enter the study at time `tenter`

```
stset tvar, fail(failure) origin(time torig) enter(time tenter)
```

Same as above, but specify analysis time in years when time variables are measured in days

```
stset tvar, fail(failure) origin(time torig) enter(time tenter) ///  
scale(365.25)
```

Convert analysis time units back to days

```
streset, scale(1)
```

Display previous `st` settings and verify that any changes to data correspond to settings

```
stset
```

Multiple-record-per-subject survival data

Specify analysis-time variable `tvar` with failure indicator `fail` and subject identifier `idvar`

```
stset tvar, failure(fail) id(idvar)
```

Same as above, and specify that subjects become at risk at time `torig`

```
stset tvar, failure(fail) id(idvar) origin(time torig)
```

Same as above, and specify that subjects enter the study at time `tenter`

```
stset tvar, failure(fail) id(idvar) origin(time torig) ///  
enter(time tenter)
```

Same as above, and specify that subjects exit the study at time `texit`

```
stset tvar, failure(fail) id(idvar) origin(time torig) ///  
enter(time tenter) exit(time texit)
```

Menu

Statistics > Survival analysis > Setup and utilities > Declare data to be survival-time data

Syntax

Single-record-per-subject survival data

```
stset timevar [if] [weight] [, single_options]

streset [if] [weight] [, single_options]

st [, nocmd notable]

stset, clear
```

Multiple-record-per-subject survival data

```
stset timevar [if] [weight], id(idvar) failure(failvar[==numlist])
    [multiple_options]

streset [if] [weight] [, multiple_options]

streset, {past|future|past future}

st [, nocmd notable]

stset, clear
```

<i>single_options</i>	Description
Main	
<code>failure(failvar[==numlist])</code>	failure event
<code>noshow</code>	prevent other st commands from showing st setting information
Options	
<code>origin(time exp)</code>	define when a subject becomes at risk
<code>scale(#)</code>	rescale time value
<code>enter(time exp)</code>	specify when subject first enters study
<code>exit(time exp)</code>	specify when subject exits study
Advanced	
<code>if(exp)</code>	select records for which <i>exp</i> is true; recommended rather than <code>if exp</code>
<code>time0(varname)</code>	mechanical aspect of interpretation about records in dataset; seldom used

<i>multiple_options</i>	Description
Main	
* id (<i>idvar</i>)	multiple-record ID variable
* failure (<i>failvar</i> [== <i>numlist</i>])	failure event
noshow	prevent other st commands from showing st setting information
Options	
origin ([<i>varname</i> == <i>numlist</i>] time <i>exp</i> min)	define when a subject becomes at risk
scale (#)	rescale time value
enter ([<i>varname</i> == <i>numlist</i>] time <i>exp</i>)	specify when subject first enters study
exit (failure [<i>varname</i> == <i>numlist</i>] time <i>exp</i>)	specify when subject exits study
Advanced	
if (<i>exp</i>)	select records for which <i>exp</i> is true; recommended rather than if <i>exp</i>
ever (<i>exp</i>)	select subjects for which <i>exp</i> is ever true
never (<i>exp</i>)	select subjects for which <i>exp</i> is never true
after (<i>exp</i>)	select records within subject on or after the first time <i>exp</i> is true
before (<i>exp</i>)	select records within subject before the first time <i>exp</i> is true
time0 (<i>varname</i>)	mechanical aspect of interpretation about records in dataset; seldom used

* **id**() and **failure**() are required with **stset** multiple-record-per-subject survival data.

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

Examples

```
. stset ftime (time measured from 0, all failed)
. stset ftime, failure(died) (time measured from 0, censoring)
. stset ftime, failure(died) id(id) (time measured from 0, censoring & ID)
. stset ftime, failure(died==2,3) (time measured from 0, failure codes)
. stset ftime, failure(died) origin(time dob) (time measured from dob, censoring)
```

You cannot harm your data by using **stset**, so feel free to experiment.

Options

Options are presented under the following headings:

Options for use with stset and streset
Options unique to streset
Options for st

Options for use with stset and streset

Main

`id(idvar)` specifies the subject-ID variable; observations with equal, nonmissing values of *idvar* are assumed to be the same subject. *idvar* may be string or numeric. Observations for which *idvar* is missing (. or "") are ignored.

When `id()` is not specified, each observation is assumed to represent a different subject and thus constitutes a one-record-per-subject survival dataset.

When you specify `id()`, the data are said to be multiple-record data, even if it turns out that there is only one record per subject. Perhaps they would better be called potentially multiple-record data.

If you specify `id()`, `stset` requires that you specify `failure()`.

Specifying `id()` never hurts; we recommend it because a few `st` commands, such as `stsplit`, require an ID variable to have been specified when the dataset was `stset`.

`failure(failvar[==numlist])` specifies the failure event.

If `failure()` is not specified, all records are assumed to end in failure. This is allowed with single-record data only.

If `failure(failvar)` is specified, *failvar* is interpreted as an indicator variable; 0 and missing mean censored, and all other values are interpreted as representing failure.

If `failure(failvar==numlist)` is specified, records with *failvar* taking on any of the values in *numlist* are assumed to end in failure, and all other records are assumed to be censored.

`noshow` prevents other `st` commands from showing the key `st` variables at the top of their output.

Options

`origin([varname==numlist] time exp | min)` and `scale(#)` define analysis time; that is, `origin()` defines when a subject becomes at risk. Subjects become at risk when `time = origin()`. All analyses are performed in terms of time since becoming at risk, called analysis time.

Let us use the terms *time* for how time is recorded in the data and *t* for analysis time. Analysis time *t* is defined

$$t = \frac{\text{time} - \text{origin}()}{\text{scale}()}$$

t is time from origin in units of scale.

By default, `origin(time 0)` and `scale(1)` are assumed, meaning that $t = \text{time}$. Then you must ensure that *time* in your data is measured as time since becoming at risk. Subjects are exposed at $t = \text{time} = 0$ and later fail. Observations with $t = \text{time} \leq 0$ are ignored because information before becoming at risk is irrelevant.

`origin()` determines when the clock starts ticking. `scale()` plays no substantive role, but it can be handy for making *t* units more readable (such as converting days to years).

`origin(time exp)` sets the origin to *exp*. For instance, if *time* were recorded as dates, such as 05jun1998, in your data and variable `expdate` recorded the date when subjects were exposed, you could specify `origin(time expdate)`. If instead all subjects were exposed on 12nov1997, you could specify `origin(time mdy(11,12,1997))`.

`origin(time exp)` may be used with single- or multiple-record data.

`origin(varname==numlist)` is for use with multiple-record data; it specifies the origin indirectly. If *time* were recorded as dates in your data, variable `obsdate` recorded the (ending) date associated with each record, and subjects became at risk upon, say, having a certain operation—and that operation were indicated by `code==217`—then you could specify `origin(code==217)`. `origin(code==217)` would mean, for each subject, that the origin time is the earliest time at which `code==217` is observed. Records before that would be ignored (because $t < 0$). Subjects who never had `code==217` would be ignored entirely.

`origin(varname==numlist time exp)` sets the origin to the later of the two times determined by `varname==numlist` and `exp`.

`origin(min)` sets origin to the earliest time observed, minus 1. This is an odd thing to do and is described in [example 10](#).

`origin()` is an important concept; see [Key concepts](#), [Two concepts of time](#), and [The substantive meaning of analysis time](#).

`scale()` makes results more readable. If you have *time* recorded in days (such as Stata dates, which are really days since 01jan1960), specifying `scale(365.25)` will cause results to be reported in years.

`enter([varname==numlist] time exp)` specifies when a subject first comes under observation, meaning that any failures, were they to occur, would be recorded in the data.

Do not confuse `enter()` and `origin()`. `origin()` specifies when a subject first becomes at risk. In many datasets, becoming at risk and coming under observation are coincident. Then it is sufficient to specify `origin()`.

`enter(time exp)`, `enter(varname==numlist)`, and `enter(varname==numlist time exp)` follow the same syntax as `origin()`. In multiple-record data, both `varname==numlist` and `time exp` are interpreted as the earliest time implied, and if both are specified, the later of the two times is used.

`exit(failure | [varname==numlist] time exp)` specifies the latest time under which the subject is both under observation and at risk. The emphasis is on latest; obviously, subjects also exit the risk pool when their data run out.

`exit(failure)` is the default. When the first failure event occurs, the subject is removed from the analysis risk pool, even if the subject has subsequent records in the data and even if some of those subsequent records document other failure events. Specify `exit(time .)` if you wish to keep all records for a subject after failure. You want to do this if you have multiple-failure data.

`exit(varname==numlist)`, `exit(time exp)`, and `exit(varname==numlist time exp)` follow the same syntax as `origin()` and `enter()`. In multiple-record data, both `varname==numlist` and `time exp` are interpreted as the earliest time implied. `exit` differs from `origin()` and `enter()` in that if both are specified, the earlier of the two times is used.

Advanced

`if(exp)`, `ever(exp)`, `never(exp)`, `after(exp)`, and `before(exp)` select relevant records.

`if(exp)` selects records for which `exp` is true. We strongly recommend specifying this `if()` option rather than `if exp` following `stset` or `streset`. They differ in that `if exp` removes the data from consideration before calculating beginning and ending times and other quantities. The `if()` option, on the other hand, sets the restriction after all derived variables are calculated. See [if\(\) versus if exp](#).

`if()` may be specified with single- or multiple-record data. The remaining selection options are for use with multiple-record data only.

`ever(exp)` selects only subjects for which `exp` is ever true.

`never(exp)` selects only subjects for which `exp` is never true.

`after(exp)` selects records within subject on or after the first time `exp` is true.

`before(exp)` selects records within subject before the first time `exp` is true.

`time0(varname)` is seldom specified because most datasets do not contain this information. `time0()` should be used exclusively with multiple-record data, and even then you should consider whether `origin()` or `enter()` would be more appropriate.

`time0()` specifies a mechanical aspect of interpretation about the records in the dataset, namely, the beginning of the period spanned by each record. See *Intermediate exit and reentry times (gaps)*.

Options unique to `stset`

`past` expands the `stset` sample to include the entire recorded past of the relevant subjects, meaning that it includes observations before becoming at risk and those excluded because of `after()`, etc.

`future` expands the `stset` sample to include the records on the relevant subjects after the last record that previously was included, if any, which typically means to include all observations after failure or censoring.

`past future` expands the `stset` sample to include all records on the relevant subjects.

Typing `streset` without arguments resets the sample to the analysis sample. See *Past and future records* for more information.

Options for `st`

`nocmd` suppresses displaying the last `stset` command.

`notable` suppresses displaying the table summarizing what has been `stset`.

Remarks and examples

[stata.com](http://www.stata.com)

Remarks are presented under the following headings:

What are survival-time data?

Key concepts

Survival-time datasets

Using stset

Two concepts of time

The substantive meaning of analysis time

Setting the failure event

Setting multiple failures

First entry times

Final exit times

Intermediate exit and reentry times (gaps)

if() versus if exp

Past and future records

Using streset

Performance and multiple-record-per-subject datasets

Sequencing of events within t

Weights

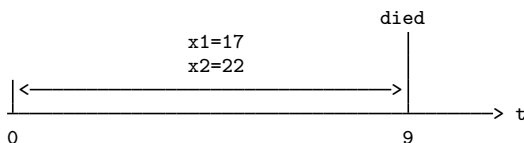
Data warnings and errors flagged by stset

Using survival-time data in Stata

Video example

What are survival-time data?

Survival-time data—what we call *st data*—document spans of time ending in an event. For instance,

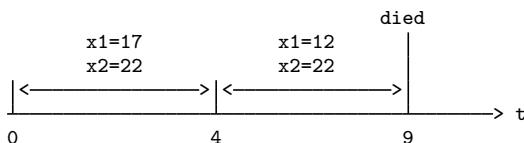


which indicates $x_1 = 17$ and $x_2 = 22$ over the time span 0 to 9, and `died = 1`. More formally, it means $x_1 = 17$ and $x_2 = 22$ for $0 < t \leq 9$, which we often write as $(0, 9]$. However you wish to say it, this information might be recorded by the observation

id	end	x1	x2	died
101	9	17	22	1

and we call this single-record survival data.

The data can be more complicated. For instance, we might have



meaning

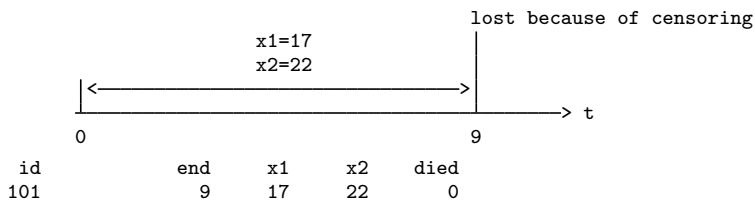
$x_1 = 17$ and $x_2 = 22$ during $(0, 4]$
 $x_1 = 12$ and $x_2 = 22$ during $(4, 9]$, and then `died = 1`.

and this would be recorded by the data

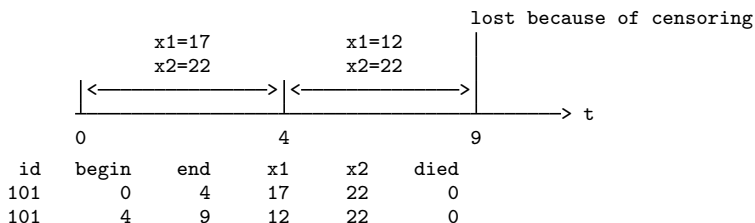
id	begin	end	x1	x2	died
101	0	4	17	22	0
101	4	9	12	22	1

We call this multiple-record survival data.

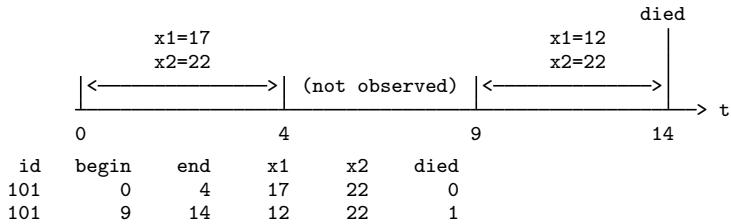
These two formats allow you to record many different possibilities. The last observation on a person need not be failure,



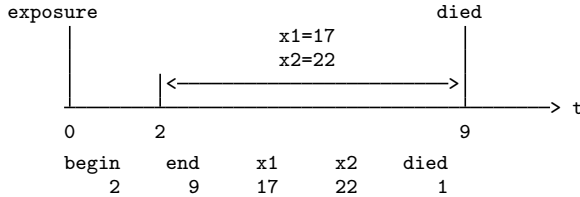
or



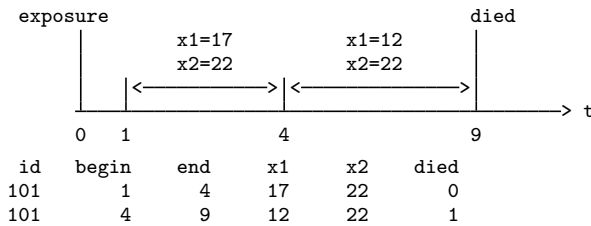
Multiple-record data might have gaps,



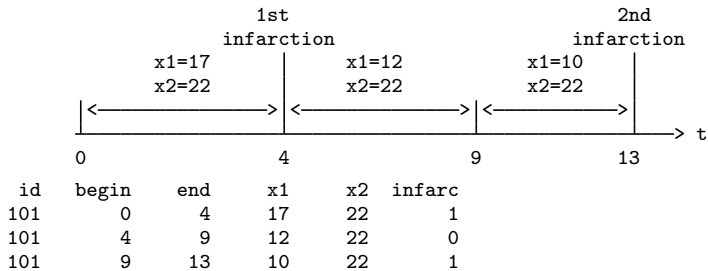
or subjects might not be observed from the onset of risk,



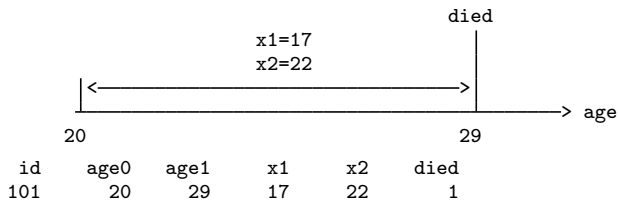
and



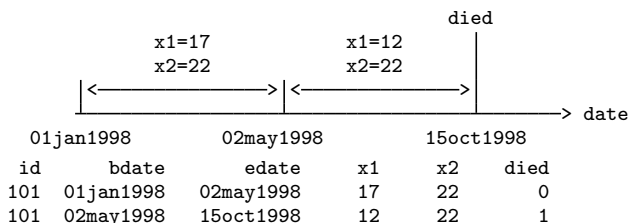
The failure event might not be death but instead something that can be repeated:



Our data may be in different time units; rather than t where $t = 0$ corresponds to the onset of risk, we might have time recorded as age,



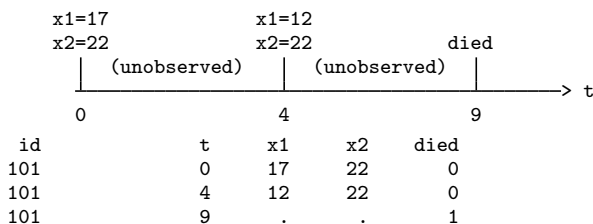
or time recorded as calendar dates:



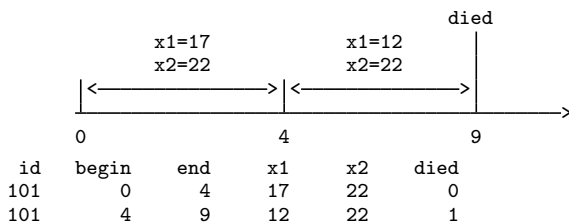
Finally, we can mix these diagrams however we wish, so we might have time recorded according to the calendar, unobserved periods after the onset of risk, subsequent gaps, and multiple failure events.

The `st` commands analyze data like these, and the first step is to tell `st` about your data by using `stset`. You do not change your data to fit some predefined mold; you describe your data with `stset`, and the rest of the `st` commands just do the right thing.

Before we discuss using `stset`, let's describe one more style of recording time-to-event data because it is common and is inappropriate for use with `st`. It is inappropriate, but it is easy to convert to the survival-time form. It is called snapshot data, which are data for which you do not know spans of time but you have information recorded at various points in time:



In this snapshot dataset, all we know are the values of `x1` and `x2` at $t = 0$ and $t = 4$, and we know that the subject died at $t = 9$. Snapshot data can be converted to survival-time data if we are willing to assume that `x1` and `x2` remained constant between times:



The `snapspan` command makes this conversion. If you have snapshot data, first see [\[ST\] snapspan](#) to convert it to survival-time data and then use `stset` to tell `st` about the converted data; see [example 10](#) first.

Key concepts

time, or, better, *time units*, is how time is recorded in your data. It might be numbers (such as 0, 1, 2, ..., with time = 0 corresponding to some exposure event), a subject's age, or calendar time.

events are things that happen at an instant in time, such as being exposed to an environmental hazard, being diagnosed as myopic, becoming employed, being promoted, becoming unemployed, having a heart attack, and dying.

failure event is the event indicating failure as it is defined for analysis. This can be a single or compound event. The failure event might be when variable `dead` is 1, or it might be when variable `diag` is any of 115, 121, or 133.

at risk means the subject is at risk of the failure event occurring. For instance, if the failure event is becoming unemployed, a person must be employed. The subject is not at risk before being employed. Once employed, the subject becomes at risk; once again, the subject is no longer at risk once the failure event occurs. If subjects become at risk upon the occurrence of some event, it is called the exposure event. Gaining employment is the exposure event in our example.

origin is the time when the subject became at risk. If time is recorded as numbers such as 0, 1, 2, . . . , with $\text{time} = 0$ corresponding to the exposure event, then $\text{origin} = 0$. Alternatively, *origin* might be the age of the subject when diagnosed or the date when the subject was exposed. Regardless, *origin* is expressed in time units.

scale is just a fixed number, typically 1, used in mapping time to analysis time t .

t , or *analysis time*, is $(\text{time} - \text{origin})/\text{scale}$, meaning the time since onset of being at risk measured in scale units.

$t = 0$ corresponds to the onset of risk, and *scale* just provides a way to make the units of t more readable. You might have time recorded in days from 01jan1960 and want t recorded in years, in which case *scale* would be 365.25.

Time is how time is recorded in your data, and t is how time is reported in the analysis.

under observation means that, should the failure event occur, it would be observed and recorded in the data. Sometimes subjects are under observation only after they are at risk. This would be the case, for instance, if subjects enrolled in a study after being diagnosed with cancer and if, to enroll in the study, subjects were required to be diagnosed with cancer.

Being under observation does not mean that the subject is necessarily at risk. A subject may come under observation before being at risk, and in fact, a subject under observation may never become at risk.

entry time and *exit time* mark when a subject is first and last under observation. The emphasis here is on the words *first* and *last*; entry time and exit time do not record observational gaps; there is only one entry time and one exit time per subject.

Entry time and exit time might be expressed as times (recorded in time units), or they might correspond to the occurrence of some event (such as enrolling in the study).

Often the entry time corresponds to $t = 0$; that is, because $t = (\text{time} - \text{origin})/\text{scale}$, $\text{time} = \text{origin}$, meaning that time equals when the subject became at risk.

Often the exit time corresponds to when the failure event occurs or, failing that, the end of data for the subject.

delayed entry means that entry time corresponds to $t > 0$; the subject became at risk before coming under observation.

ID refers to a subject identification variable; equal values of *ID* indicate that the records are on the same subject. An *ID* variable is required for multiple-record data and is optional, but recommended, with single-record data.

time0 refers to the beginning time (recorded in time units) of a record. Some datasets have this variable, but most do not. If the dataset does not contain the beginning time for each record, subsequent records are assumed to begin where previous records ended. A *time0* variable may be created for these datasets by using the `snapspan` command; see [ST] [snapspan](#). Do not confuse *time0*—a mechanical aspect of datasets—with entry time—a substantive aspect of analysis.

gaps refer to gaps in observation between entry time and exit time. During a gap, a subject is not under observation. Gaps can arise only if the data contain a `time0` variable, because otherwise subsequent records beginning when previous records end would preclude there being gaps in the data. Gaps are distinct from delayed entry.

past history is a term we use to mean information recorded in the data before the subject was both at risk and under observation. Complex datasets can contain such observations. Say that the dataset contains histories on subjects from birth to death. You might tell `st` that a subject becomes at risk once diagnosed with a particular kind of cancer. The past history on the subject would then refer to records before the subject was diagnosed.

The word *history* is often dropped, and the term simply becomes *past*. For instance, we might want to know whether the subject smoked in the past.

future history is a term meaning information recorded in the data after the subject is no longer at risk. Perhaps the failure event is not so serious as to preclude the possibility of data after failure.

The word *history* is often dropped, and the term simply becomes *future*. Perhaps the failure event is cardiac infarction, and you want to know whether the subject died soon in the future so that you can exclude the subject.

Survival-time datasets

In survival-time datasets, observations (records) document a span of time. The span might be explicitly indicated, such as

```
begin   end   x1   x2
  3     9   17   22      <- spans (3,9]
```

or it might be implied that the record begins at 0,

```
end     x1   x2
  9     17   22      <- spans (0,9]
```

or it might be implied because there are multiple records per subject:

```
id     end   x1   x2
  1     4   17   22      <- spans (0,4]
  1     9   12   22      <- spans (4,9]
```

Records may have an event indicator:

```
begin   end   x1   x2   died
  3     9   17   22     1      <- spans (3,9], died at t=9

end     x1   x2   died
  9     17   22     1      <- spans (0,9], died at t=9

id     end   x1   x2   died
  1     4   17   22     0      <- spans (0,4],
  1     9   12   22     1      <- spans (4,9], died at t=9
```

The first two examples are called single-record survival-time data because there is one record per subject.

The final example is called multiple-record survival-time data. There are two records for the subject with `id = 1`.

Either way, survival-time data document time spans. Characteristics are assumed to remain constant over the span, and the event is assumed to occur at the end of the span.

Using stset

Once you have `stset` your data, you can use the other `st` commands.

If you save your data after `stsetting`, you will not have to re-`stset` in the future; Stata will remember.

`stset` declares your data to be survival-time data. It does not change the data, although it does add a few variables to your dataset.

This means that you can re-`stset` your data as often as you wish. In fact, the `streset` command encourages this. Using complicated datasets often requires typing long `stset` commands, such as

```
. stset date, fail(event==27 28) origin(event==15) enter(event==22)
```

Later, you might want to try `fail(event==27)`. You could retype the `stset` command, making the substitution, or you could type

```
. streset, fail(event==27)
```

`streset` takes what you type, merges it with what you have previously declared with `stset`, and performs the combined `stset` command.

► Example 1: Single-record data

Generators are run until they fail. Here is some of our dataset:

```
. use https://www.stata-press.com/data/r18/kva
(Generator experiment)
. list in 1/3
```

	failtime	load	bearings
1.	100	15	0
2.	140	15	1
3.	97	20	0

The `stset` command for this dataset is

```
. stset failtime
Survival-time data settings
    Failure event: (assumed to fail at time=failtime)
Observed time interval: (0, failtime]
Exit on or before: failure
```

```
    12 total observations
    0  exclusions
```

```
    12 observations remaining, representing
    12 failures in single-record/single-failure data
    896 total analysis time at risk and under observation
                At risk from t =           0
    Earliest observed entry t =           0
                Last observed exit t =      140
```

When you type `stset timevar`, `timevar` is assumed to be the time of failure. More generally, you will learn, `timevar` is the time of failure or censoring. Here `timevar` is `failtime`.

```
. describe
Contains data from https://www.stata-press.com/data/r18/kva.dta
Observations:      12      Generator experiment
Variables:         7       8 Jan 2022 15:59
```

Variable name	Storage type	Display format	Value label	Variable label
failtime	int	%9.0g		Time until failure (hrs.)
load	byte	%9.0g		Overload (kVA)
bearings	byte	%9.0g		Has new bearings
_st	byte	%8.0g		1 if record is to be used; 0 otherwise
_d	byte	%8.0g		1 if failure; 0 if censored
_t	int	%10.0g		Analysis time when record ends
_t0	byte	%10.0g		Analysis time when record begins

Sorted by:

When you `stset` this dataset, Stata added the system variables `_st`, `_d`, `_t`, and `_t0` to your data.



► Example 2: Single-record data with censoring

Generators are run until they fail, but during the experiment, the room flooded, so some generators were run only until the flood. Here are some of our data:

```
. use https://www.stata-press.com/data/r18/kva2
(Generator experiment)
. list in 1/4
```

	failtime	load	bearings	failed
1.	100	15	0	1
2.	140	15	1	0
3.	97	20	0	1
4.	122	20	1	1

Here the second generator did not fail at time 140; the experiment was merely discontinued then. The `stset` command for this dataset is

```
. stset failtime, failure(failed)
Survival-time data settings
      Failure event: failed!=0 & failed<.
Observed time interval: (0, failtime]
Exit on or before: failure
```

```
-----
      12 total observations
       0 exclusions
-----
      12 observations remaining, representing
      11 failures in single-record/single-failure data
      896 total analysis time at risk and under observation
                At risk from t =           0
      Earliest observed entry t =           0
                Last observed exit t =      140
```

When you type `stset timevar, failure(failvar)`, `timevar` is interpreted as the time of failure or censoring, which is determined by the value of `failvar`. `failvar = 0` and `failvar = .` (missing) indicate censorings, and all other values indicate failure.

◀

▷ Example 3: Multiple-record data

Assume that we are analyzing survival time of patients with a particular kind of cancer. In this dataset, the characteristics of patients vary over time, perhaps because new readings were taken or because the drug therapy was changed. Some of the data are

```
. list, separator(0)
```

	patid	t	died	x1	x2
1.	90	100	0	1	0
2.	90	150	1	0	0
3.	91	50	1	1	1
4.	92	100	0	0	0
5.	92	150	0	0	1
6.	92	190	0	0	0
7.	93	100	0	0	0

(output omitted)

There are two records for patient 90, and `died` is 0 in the first record but 1 in the second. The interpretation of these two records is

Interval (0,100]: `x1 = 1` and `x2 = 0`
 Interval (100,150]: `x1 = 0` and `x2 = 0`
 at `t = 150`: the patient died

Similarly, here is how you interpret the other records:

Patient 91:
 Interval (0, 50]: `x1 = 1` and `x2 = 1`
 at `t = 50`: the patient died

Patient 92:
 Interval (0,100]: `x1 = 0` and `x2 = 0`
 Interval (100,150]: `x1 = 0` and `x2 = 1`
 Interval (150,190]: `x1 = 0` and `x2 = 0`
 at `t = 190`: the patient was lost because of censoring

Look again at patient 92's data:

patid	t	died	x1	x2
92	100	0	0	0
92	150	0	0	1
92	190	0	0	0

`died = 0` for the first event. Mechanically, this removes the subject from the data at `t = 100`—the patient is treated as censored. The next record, however, adds the patient back into the data (at `t = 100`) with new characteristics.

The `stset` command for this dataset is

```
. stset t, id(patid) failure(died)
Survival-time data settings
      ID variable: patid
      Failure event: died!=0 & died<.
Observed time interval: (t[_n-1], t]
Exit on or before: failure
```

```
      126 total observations
       0 exclusions
```

```
      126 observations remaining, representing
       40 subjects
        26 failures in single-failure-per-subject data
    2,989 total analysis time at risk and under observation
                                     At risk from t =          0
      Earliest observed entry t =          0
      Last observed exit t =          139
```

When you have multiple-record data, you specify `stset`'s `id(idvar)` option. When you type `stset timevar, id(idvar) failure(failvar)`, `timevar` denotes the end of the period (just as it does in single-record data). The first record within `idvar` is assumed to begin at time 0, and later records are assumed to begin where the previous record left off. `failvar` should contain 0 on all but, possibly, the last record within `idvar`, unless your data contain multiple failures (in which case you must specify the `exit()` option; see [Setting multiple failures](#) below).

◀

▷ Example 4: Multiple-record data with multiple events

We have the following data on hospital patients admitted to a particular ward:

patid	day	sex	x1	x2	code
101	5	1	10	10	177
101	13	1	20	8	286
101	21	1	16	11	208
101	24	1	11	17	401
102	8	0	20	19	204
102	18	0	19	1	401
103	<i>etc.</i>				

Variable code records various actions; code 401 indicates being discharged alive, and 402 indicates death. We `stset` this dataset by typing

```
. stset day, id(patid) fail(code==402)
Survival-time data settings
      ID variable: patid
      Failure event: code==402
Observed time interval: (day[_n-1], day]
Exit on or before: failure
```

```
      243 total observations
       0 exclusions
```

```
      243 observations remaining, representing
       40 subjects
       15 failures in single-failure-per-subject data
    1,486 total analysis time at risk and under observation
                                     At risk from t =          0
      Earliest observed entry t =          0
      Last observed exit t =          62
```

When you specify `failure(eventvar==#)`, the failure event is as specified. You may include a list of numbers following the equal signs. If failure were codes 402 and 403, you could specify `failure(code==402 403)`. If failure were codes 402, 403, 404, 405, 406, 407, and 409, you could specify `failure(code==402/407 409)`.

◀

► Example 5: Multiple-record data recording time rather than t

More reasonably, the hospital data in the above example would not contain days since admission but would contain admission and current dates. In the dataset below, `adday` contains the day of admission, and `curday` contains the ending date of the record, both recorded as number of days since the ward opened:

patid	adday	curday	sex	x1	x2	code
101	287	292	1	10	10	177
101	.	300	1	20	8	286
101	.	308	1	16	11	208
101	.	311	1	11	17	401
102	289	297	0	20	19	204
102	.	307	0	19	1	401
103	etc.					

This is the same dataset as shown in [example 4](#). Previously, the first record on patient 101 was recorded 5 days after admission. In this dataset, $292 - 287 = 5$. We would `stset` this dataset by typing

```
. stset curday, id(patid) fail(code==402) origin(time adday)
Survival-time data settings
      ID variable: patid
      Failure event: code==402
Observed time interval: (curday[_n-1], curday]
Exit on or before: failure
Time for analysis: (time-origin)
Origin: time adday
```

```
243 total observations
  0 ignored because never entered
```

```
243 observations remaining, representing
 40 subjects
 15 failures in single-failure-per-subject data
1,486 total analysis time at risk and under observation
                At risk from t =          0
                Earliest observed entry t =      0
                Last observed exit t =          62
```

`origin()` sets when a subject becomes at risk. It does this by defining analysis time.

When you specify `stset timevar, ... origin(time originvar)`, analysis time is defined as $t = (timevar - originvar)/scale()$. In analysis-time units, subjects become at risk at $t = 0$. See [Two concepts of time](#) and [The substantive meaning of analysis time](#) below. ◀

▶ Example 6: Multiple-record data with time recorded as a date

Even more reasonably, dates would not be recorded as integers 428, 433, and 453, meaning the number of days since the ward opened. The dates would be recorded as dates:

```
patid    addate    curdate    sex    x1    x2    code
101 18aug1998 23aug1998    1     10    10    177
101      .    31aug1998    1     20     8    286
101      .    08sep1998    1     16    11    208
101      .    11sep1998    1     11    17    401
102 20aug1998 28aug1998    0     20    19    204
102      .    07sep1998    0     19     1    401
103      etc.
```

That, in fact, changes nothing. We still type what we previously typed:

```
. stset curdate, id(patid) fail(code==402) origin(time addate)
```

Stata dates are, in fact, integers—they are the number of days since 01jan1960—and it is merely Stata's `%td` display format that makes them display as dates. ◀

▶ Example 7: Multiple-record data with extraneous information

Perhaps we wish to study the outcome after a certain operation, said operation being indicated by code 286. Subjects become at risk when the operation is performed. Here we do not type

```
. stset curdate, id(patid) fail(code==402) origin(time addate)
```

We instead type

```
. stset curdate, id(patid) fail(code==402) origin(code==286)
```

The result of typing this would be to set analysis time t to

$$t = \text{curdate} - (\text{the value of curdate when code}==286)$$

Let's work through this for the first patient:

patid	addate	curdate	sex	x1	x2	code
101	18aug1998	23aug1998	1	10	10	177
101	.	31aug1998	1	20	8	286
101	.	08sep1998	1	16	11	208
101	.	11sep1998	1	11	17	401

The event 286 occurred on 31aug1998, and thus the values of t for the four records are

$$t_1 = \text{curdate}_1 - 31\text{aug}1998 = 23\text{aug}1998 - 31\text{aug}1998 = -8$$

$$t_2 = \text{curdate}_2 - 31\text{aug}1998 = 31\text{aug}1998 - 31\text{aug}1998 = 0$$

$$t_3 = \text{curdate}_3 - 31\text{aug}1998 = 08\text{sep}1998 - 31\text{aug}1998 = 8$$

$$t_4 = \text{curdate}_4 - 31\text{aug}1998 = 11\text{sep}1998 - 31\text{aug}1998 = 11$$

Information prior to $t = 0$ is not relevant because the subject is not yet at risk. Thus the relevant data on this subject are

t in $(0, 8]$ sex = 1, x1 = 16, x2 = 11

t in $(8, 11]$ sex = 1, x1 = 11, x2 = 17, and the subject is censored (code \neq 402)

That is precisely the logic that `stset` went through. For your information, `stset` quietly creates the variables

<code>_st</code>	1 if the record is to be used, 0 if ignored
<code>_t0</code>	Analysis time when record begins
<code>_t</code>	Analysis time when record ends
<code>_d</code>	1 if failure, 0 if censored

You can examine these variables after issuing the `stset` command:

```
. list _st _t0 _t _d
```

	<code>_st</code>	<code>_t0</code>	<code>_t</code>	<code>_d</code>
1.	0	.	.	.
2.	0	.	.	.
203.	1	0	8	0
204.	1	8	11	0

Results are just as we anticipated. Do not let the observation numbers bother you; `stset` sorts the data in a way it finds convenient. Feel free to re-sort the data; if any of the `st` commands need the data in a different order, they will sort it themselves.

There are two ways of specifying `origin()`:

```
origin(time timevar)    or    origin(time exp)
origin(eventvar==numlist)
```

In the first syntax—which is denoted by typing the word `time`—you directly specify when a subject becomes at risk. In the second syntax—which is denoted by typing a variable name and equal signs—you specify the same thing indirectly. The subject becomes at risk when the specified event occurs (which may be never).

Information prior to `origin()` is ignored. That information composes what we call the past history. ◀

▷ Example 8: Multiple-record data with delayed entry

In another analysis, we want to use the above data to analyze all patients, not just those undergoing a particular operation. In this analysis, subjects become at risk when they enter the ward. For this analysis, however, we need information from a particular test, and that information is available only if the test is administered to the patient. Even if the test is administered, some amount of time passes before that. Assume that when the test is administered, `code==152` is inserted into the patient's hospital record.

To summarize, we want `origin(time addate)`, but patients do not enter our sample until `code==152`. The way to `stset` these data is

```
. stset curdate, id(patid) fail(code==402) origin(time addate) enter(code==152)
```

Patient 107 has code 152:

patid	addate	curdate	sex	x1	x2	code
107	22aug1998	25aug1998	1	9	13	274
107	.	28aug1998	1	19	19	152
107	.	30aug1998	1	18	12	239
107	.	07sep1998	1	12	11	401

In analysis time, $t = 0$ corresponds to 22aug1998. The test was not administered, however, until 6 days later. The analysis times for these records are

$$t_1 = \text{curdate}_1 - 22\text{aug}1998 = 25\text{aug}1998 - 22\text{aug}1998 = 3$$

$$t_2 = \text{curdate}_2 - 22\text{aug}1998 = 28\text{aug}1998 - 22\text{aug}1998 = 6$$

$$t_3 = \text{curdate}_3 - 22\text{aug}1998 = 30\text{aug}1998 - 22\text{aug}1998 = 8$$

$$t_4 = \text{curdate}_4 - 22\text{aug}1998 = 07\text{sep}1998 - 22\text{aug}1998 = 16$$

and the data we want in our sample are

t in (6, 8] `sex = 1, x1 = 18, x2 = 12`

t in (8, 16] `sex = 1, x1 = 12, x2 = 11`, and patient was censored (`code ≠ 402`)

The above `stset` command produced this:

```
. list _st _t0 _t _d
```

	_st	_t0	_t	_d
1.	0	.	.	.
2.	0	.	.	.
39.	1	6	8	0
40.	1	8	16	0

▷ Example 9: Multiple-record data with extraneous information and delayed entry

The `origin()` and `enter()` options can be combined. For instance, we want to analyze patients receiving a particular operation (time at risk begins upon `code == 286`, but patients may not enter the sample before a test is administered, denoted by `code == 152`). We type

```
. stset curdate, id(patid) fail(code==402) origin(code==286) enter(code==152)
```

If we typed the above commands, it would not matter whether the test was performed before or after the operation.

A patient who had the test and then the operation would enter at analysis time $t = 0$.

A patient who had the operation and then the test would enter at analysis time $t > 0$, the analysis time being the time the test was performed.

If we wanted to require that the operation be performed after the test, we could type

```
. stset curdate, id(patid) fail(code==402) origin(code==286) after(code==152)
```

Admittedly, this can be confusing. The way to proceed is to find a complicated case in your data and then list `_st _t0 _t _d` for that case after you `stset` the data.

◀

▷ Example 10: Real data

All of our hospital ward examples are artificial in one sense: it is unlikely the data would have come to us in survival-time form:

patid	addate	curdate	sex	x1	x2	code
101	18aug1998	23aug1998	1	10	10	177
101	.	31aug1998	1	20	8	286
101	.	08sep1998	1	16	11	208
101	.	11sep1998	1	11	17	401
102	20aug1998	28aug1998	0	20	19	204
102	.	07sep1998	0	19	1	401
103	<i>etc.</i>					

Rather, we would have received a snapshot dataset:

patid	date	sex	x1	x2	code	
101	18aug1998	1	10	10	22	
101	23aug1998	.	20	8	177	
101	31aug1998	.	16	11	286	
101	08sep1998	.	11	17	208	
101	11sep1998	.	.	.	401	
102	20aug1998	0	20	19	22	
102	28aug1998	.	19	1	204	
102	07sep1998	.	.	.	401	
103	<i>etc.</i>					

In a snapshot dataset, we have a time (here a date) and values of the variables as of that instant.

This dataset can be converted to the appropriate form by typing

```
. snapspan patid date code
```

The result would be as follows:

patid	date	sex	x1	x2	code
101	18aug1998	.	.	.	22
101	23aug1998	1	10	10	177
101	31aug1998	.	20	8	286
101	08sep1998	.	16	11	208
101	11sep1998	.	11	17	401
102	20aug1998	.	.	.	22
102	28aug1998	0	20	19	204
102	07sep1998	.	19	1	401

This is virtually the same dataset with which we have been working, but it differs in two ways:

1. The variable `sex` is not filled in for all the observations because it was not filled in on the original form. The hospital wrote down the sex on admission and then never bothered to document it again.
2. We have no admission date (`addate`) variable. Instead, we have an extra first record for each patient with `code = 22` (22 is the code the hospital uses for admissions).

The first problem is easily fixed, and the second, it turns out, is not a problem because we can vary what we type when we `stset` the data.

First, let's fix the problem with variable `sex`. There are two ways to proceed. One would be simply to fill in the variable ourselves:

```
. by patid (date), sort: replace sex = sex[_n-1] if sex>=.
```

We could also perform a phony `stset` that is good enough to set all the data and then use `stfill` to fill in the variable for us. Let's begin with the phony `stset`:

```
. stset date, id(patid) origin(min) fail(code== -1)
```

```
Survival-time data settings
```

```
    ID variable: patid
```

```
    Failure event: code== -1
```

```
Observed time interval: (date[_n-1], date]
```

```
Exit on or before: failure
```

```
Time for analysis: (time-origin)
```

```
Origin: min
```

```
283 total observations
```

```
0 exclusions
```

```
283 observations remaining, representing
```

```
40 subjects
```

```
0 failures in single-failure-per-subject data
```

```
2,224 total analysis time at risk and under observation
```

```
At risk from t = 0
```

```
Earliest observed entry t = 0
```

```
Last observed exit t = 89
```

Typing `stset date, id(patid) origin(min) fail(code== -1)` does not produce anything we would want to use for analysis. This is a trick to get the dataset temporarily `stset` so that we can use some `st` data management commands on it.

The first part of the trick is to specify `origin(min)`. This defines the analysis time as $t = 0$, corresponding to the minimum observed value of the time variable minus 1. The time variable is `date` here. Why the minimum minus 1? Because `st` ignores observations for which analysis time $t < 0$. `origin(min)` provides a phony definition of t that ensures $t > 0$ for all observations.

The second part of the trick is to specify `fail(code == -1)`, and you might have to vary what you type. We just wanted to choose an event that we know never happens, thus ensuring that no observations are ignored after failure.

Now that we have the dataset `stset`, we can use the other `st` commands. Do not use the `st` analysis commands unless you want ridiculous results, but one of the `st` data management commands is just what we want:

```
. stfill sex, forward
      Failure _d: code==-1
      Analysis time _t: (date-origin)
      Origin: min
      ID variable: patid
Replacing missing values with previously observed values:
      sex: 203 real changes made
```

Problem one solved.

The second problem concerns the lack of an admission-date variable. That is not really a problem because we have a new first observation with `code = 22` recording the date of admission, so every place we previously coded `origin(time addate)`, we substitute `origin(code == 22)`.

Problem two solved.

We also solved the big problem—converting a snapshot dataset into a survival-time dataset; see [\[ST\] `snapspan`](#).

◀

Two concepts of time

The `st` system has two concepts of time. The first is *time* in italics, which corresponds to how time is recorded in your data. The second is analysis time, which we write as *t*. Substantively, analysis time is time at risk. `stset` defines analysis time in terms of *time* via

$$t = \frac{\text{time} - \text{origin}()}{\text{scale}()}$$

t and *time* can be the same thing, and by default they are because, by default, `origin()` is 0 and `scale()` is 1.

All the `st` analysis commands work with analysis time, *t*.

By default, if you do not specify the `origin()` and `scale()` options, your time variables are expected to be the analysis-time variables. This means that *time* = 0 corresponds to when subjects became at risk, and that means, among other things, that observations for which *time* < 0 are ignored because survival analysis concerns persons who are at risk, and no one is at risk before *t* = 0.

`origin` determines when the clock starts ticking. If you do not specify `origin()`, `origin(time 0)` is assumed, meaning that *t* = *time* and that persons are at risk from *t* = *time* = 0.

time and *t* will often differ. *time* might be calendar time and *t* the length of time since some event, such as being born or being exposed to some risk factor. `origin()` sets when *t* = 0. `scale()` merely sets a constant that makes *t* more readable.

The syntax for the `origin()` option makes it look more complicated than it really is

```
origin([varname == numlist] time exp | min)
```

This says that there are four different ways to specify `origin()`:

```
origin(time exp)
origin(varname == numlist)
origin(varname == numlist time exp)
origin(min)
```

The first syntax can be used with single- or multiple-record data. It states that the origin is given by *exp*, which can be a constant for all observations, a variable (and hence may vary subject by subject), or even an expression composed of variables and constants. Perhaps the origin is a fixed date or a date recorded in the data when the subject was exposed or when the subject turned 18.

The second and third syntaxes are for use with multiple-record data. The second states that the origin corresponds to the (earliest) time when the designated event occurred. Perhaps the origin is when an operation was performed. The third syntax calculates the origin both ways and then selects the later one.

The fourth syntax does something odd; it sets the origin to the minimum time observed minus 1. This is not useful for analysis but is sometimes useful for playing data management tricks; see [example 10](#) above.

Let's start with the first syntax. Say that you had the data

faildate	x1	x2
28dec1997	12	22
12nov1997	15	22
03feb1998	55	22

and that all the observations came at risk on the same date, 01nov1997. You could type

```
. stset faildate, origin(time mdy(11,1,1997))
```

Remember that `stset` adds `_t0` and `_t` to your dataset and that they contain the time span for each record, documented in analysis-time units. After typing `stset`, you can list the results:

```
. list faildate x1 x2 _t0 _t
```

	faildate	x1	x2	_t0	_t
1.	28dec1997	12	22	0	57
2.	12nov1997	15	22	0	11
3.	03feb1998	55	22	0	94

Record 1 reflects the period $(0, 57]$ in analysis-time units, which are days here. `stset` calculated the 57 from $28\text{dec}1997 - 01\text{nov}1997 = 13,876 - 13,819 = 57$. (Dates such as 28dec1997 are really just integers containing the number of days from 01jan1960, and Stata's `%td` display format makes them display nicely. 28dec1997 is really the number 13,876.)

As another example, we might have data recording exposure and failure dates:

expdate	faildate	x1	x2
07may1998	22jun1998	12	22
02feb1998	11may1998	11	17

The way to `stset` this dataset is

```
. stset faildate, origin(time expdate)
```

and the result, in analysis units, is

```
. list expdate faildate x1 x2 _t0 _t
```

	expdate	faildate	x1	x2	_t0	_t
1.	07may1998	22jun1998	12	22	0	46
2.	02feb1998	11may1998	11	17	0	98

There is nothing magical about dates. Our original data could just as well have been

expdate	faildate	x1	x2
32	78	12	22
12	110	11	17

and the result would still be the same because $78 - 32 = 46$ and $110 - 12 = 98$.

Specifying an expression can sometimes be useful. Suppose that your dataset has the variable `date` recording the date of event and variable `age` recording the subject's age as of `date`. You want to make $t = 0$ correspond to when the subject turned 18. You could type `origin(time date-int((age-18)*365.25))`.

`origin(varname==numlist)` is for use with multiple-record data. It states when each subject became at risk indirectly; the subject became at risk at the earliest time that `varname` takes on any of the enumerated values. Say that you had

patid	date	x1	x2	event
101	12nov1997	15	22	127
101	28dec1997	12	22	155
101	03feb1998	55	22	133
101	05mar1998	14	22	127
101	09apr1998	12	22	133
101	03jun1998	13	22	101
102	22nov1997	.	.	.

and assume `event = 155` represents the onset of exposure. You might `stset` this dataset by typing

```
. stset date, id(patid) origin(event==155) ...
```

If you did that, the information for patient 101 before 28dec1997 would be ignored in subsequent analysis. The prior information would not be removed from the dataset; it would just be ignored. Probably something similar would happen for patient 102, or if patient 102 has no record with `event = 155`, all the records on the patient would be ignored.

For analysis time, $t = 0$ would correspond to when event 155 occurred. Here are the results in analysis-time units:

patid	date	x1	x2	event	_t0	_t
101	12nov1997	15	22	127	.	.
101	28dec1997	12	22	155	.	.
101	03feb1998	55	22	133	0	37
101	05mar1998	14	22	127	37	67
101	09apr1998	12	22	133	67	102
101	03jun1998	13	22	101	102	157
102	22nov1997

Patient 101's second record is excluded from the analysis. That is not a mistake. Records document durations, `date` reflects the end of the period, and events occur at the end of periods. Thus event 155 occurred at the instant `date = 28dec1997`, and the relevant first record for the patient is `(28dec1997, 03feb1998]` in time units, which is `(0, 37]` in t units.

The substantive meaning of analysis time

In specifying `origin()`, you must ask yourself whether two subjects with identical characteristics face the same risk of failure. The answer is that they face the same risk when they have the same value of $t = (\text{time} - \text{origin()})/\text{scale}()$ or, equivalently, when the same amount of time has elapsed from `origin()`.

Say that we have the following data on smokers who have died:

ddate	x1	x2	reason
11mar1984	23	11	2
15may1994	21	9	1
22nov1993	22	13	2
<i>etc.</i>			

We wish to analyze death due to `reason==2`. However, typing

```
. stset ddate, fail(reason==2)
```

would probably not be adequate. We would be saying that smokers were at risk of death from 01jan1960. Would it matter? It would if we planned on doing anything parametric because parametric hazard functions, except for the exponential, are functions of analysis time, and the location of 0 makes a difference.

Even if we were thinking of performing nonparametric analysis, there would probably be difficulties. We would be asserting that two "identical" persons (in terms of `x1` and `x2`) face the same risk on the same calendar date. Does the risk of death due to smoking really change as the calendar changes?

It would be more reasonable to assume that the risk changes with how long a subject has been smoking and that our data would probably include that date. We would type

```
. stset ddate, fail(reason==2) origin(time smdate)
```

if `smdate` were the name of the date-started-smoking variable. We would now be saying that the risk is equal when the number of days smoked is the same. We might prefer to see t in years,

```
. stset ddate, fail(reason==2) origin(time smdate) scale(365.25)
```

but that would make no substantive difference.

Consider single-record data on firms that went bankrupt:

incorp	bankrupt	x1	x2	btype
22jan1983	11mar1984	23	11	2
17may1992	15may1994	21	9	1
03nov1991	22nov1993	22	13	2
<i>etc.</i>				

Say that we wish to examine the risk of a particular kind of bankruptcy, `btype==2`, among firms that become bankrupt. Typing

```
. stset bankrupt, fail(btype==2)
```

would be more reasonable than it was in the smoking example. It would not be reasonable if we were thinking of performing any sort of parametric analysis, of course, because then location of $t = 0$ would matter, but it might be reasonable for semiparametric analysis. We would be asserting that two “identical” firms (with respect to the characteristics we model) have the same risk of bankruptcy when the calendar dates are the same. We would be asserting that the overall state of the economy matters.

It might be reasonable to instead measure time from the date of incorporation:

```
. stset bankrupt, fail(btype==2) origin(time incorp)
```

Understand that the choice of `origin()` is a substantive decision.

Setting the failure event

You set the failure event by using the `failure()` option.

In single-record data, if `failure()` is not specified, every record is assumed to end in a failure. For instance, with

	failtime	load	bearings
1.	100	15	0
2.	140	15	1
etc.			

you would type `stset failtime`, and the first observation would be assumed to fail at time = 100; the second, at time = 140; and so on.

`failure(varname)` specifies that a failure occurs whenever *varname* is not zero and is not missing. For instance, with

	failtime	load	bearings	burnout
1.	100	15	0	1
2.	140	15	1	0
3.	97	20	0	1
4.	122	20	1	0
5.	84	25	0	1
6.	100	25	1	1
etc.				

you might type `stset failtime, failure(burnout)`. Observations 1, 3, 5, and 6 would be assumed to fail at times 100, 97, 84, and 100, respectively; observations 2 and 4 would be assumed to be censored at times 140 and 122.

Similarly, if the data were

	failtime	load	bearings	burnout
1.	100	15	0	1
2.	140	15	1	0
3.	97	20	0	2
4.	122	20	1	.
5.	84	25	0	2
6.	100	25	1	3
etc.				

the result would be the same. Nonzero, nonmissing values of the failure variable are assumed to represent failures. (Perhaps `burnout` contains a code on how the burnout occurred.)

`failure(varname == numlist)` specifies that a failure occurs whenever *varname* takes on any of the values of *numlist*. In the above example, specifying

```
. stset failtime, failure(burnout==1 2)
```

would treat observation 6 as censored.

```
. stset failtime, failure(burnout==1 2 .)
```

would also treat observation 4 as a failure.

```
. stset failtime, failure(burnout==1/3 6 .)
```

would treat `burnout==1`, `burnout==2`, `burnout==3`, `burnout==6`, and `burnout==.` as representing failures and all other values as representing censorings. (Perhaps we want to examine “failure due to meltdown”, and these are the codes that represent the various kinds of meltdown.)

`failure()` is treated the same way in both single- and multiple-record data. Consider

	patno	t	x1	x2	died
1.	1	4	23	11	1
2.	2	5	21	9	0
3.	2	8	22	13	1
4.	3	7	20	5	0
5.	3	9	22	5	0
6.	3	11	21	5	0
7.	4	...			

Typing

```
. stset t, id(patno) failure(died)
```

would treat

patno==1	as dying	at t==4
patno==2	as dying	at t==8
patno==3	as being censored	at t==11

Intervening records on the same subject are marked as “censored”. Technically, they are not really censored if you think about it carefully; they are simply marked as not failing. Look at the data for subject 3:

	patno	t	x1	x2	died
	3	9	22	5	0
	3	11	21	5	0

The subject is not censored at $t = 9$ because there are more data on the subject; it is merely the case that the subject did not die at that time. At $t = 9$, `x1` changed from 22 to 21. The subject is really censored at $t = 11$ because the subject did not die and there are no more records on the subject.

Typing `stset t, id(patno) failure(died)` would mark the same persons as dying and the same persons as censored, as in the previous case. If `died` contained not 0 and 1, but 0 and nonzero, nonmissing codes for the reason for death would be

	patno	t	x1	x2	died
1.	1	4	23	11	103
2.	2	5	21	9	0
3.	2	8	22	13	207
4.	3	7	20	5	0
5.	3	9	22	5	0
6.	3	11	21	5	0
7.	4	...			

Typing

```
. stset t, id(patno) failure(died)
```

or

```
. stset t, id(patno) failure(died==103 207)
```

would yield the same results; subjects 1 and 2 would be treated as dying and subject 3 as censored.

Typing

```
. stset t, id(patno) failure(died==207)
```

would treat subject 2 as dying and subjects 1 and 3 as censored. Thus when you specify the values for the code, the code variable need not ever contain 0. In

	patno	t	x1	x2	died
1.	1	4	23	11	103
2.	2	5	21	9	13
3.	2	8	22	13	207
4.	3	7	20	5	11
5.	3	9	22	5	12
6.	3	11	21	5	12
7.	4	...			

typing

```
. stset t, id(patno) failure(died==207)
```

treats patient 2 as dying and 1 and 3 as censored. Typing

```
. stset t, id(patno) failure(died==103 207)
```

treats patients 1 and 2 as dying and 3 as censored.

Setting multiple failures

In multiple-record data, records after the first failure event are ignored unless you specify the `exit()` option. Consider the following data:

	patno	t	x1	x2	code
1.	1	4	21	7	14
2.	1	5	21	7	11
3.	1	7	20	7	17
4.	1	8	22	7	22
5.	1	9	22	7	22
6.	1	11	21	7	29
7.	2	...			

Perhaps code 22 represents the event of interest—say, the event “visited the doctor”. Were you to type `stset t, id(patno) failure(code==22)`, the result would be as if the data contained

	patno	t	x1	x2	code
1.	1	4	21	7	14
2.	1	5	21	7	11
3.	1	7	20	7	17
4.	1	8	22	7	22

Records after the first occurrence of the failure event are ignored. If you do not want this, you must specify the `exit()` option. Probably you would want to specify `exit(time .)`, here meaning that subjects are not to exit the risk group until their data run out. Alternatively, perhaps code 142 means “entered the nursing home” and, once that event happens, you no longer want them in the risk group. Then you would code `exit(code==142)`; see *Final exit times* below.

First entry times

Do not confuse `enter()` with `origin()`. `origin()` specifies when a subject first becomes at risk. `enter()` specifies when a subject first comes under observation. In most datasets, becoming at risk and coming under observation are coincident. Then it is sufficient to specify `origin()` alone, although you could specify both options.

Some persons enter the data after they have been at risk of failure. Say that we are studying deaths due to exposure to substance X and we know the date at which a person was first exposed to the substance. We are willing to assume that persons are at risk from the date of exposure forward. A person arrives at our door who was exposed 15 years ago. Can we add this person to our data? The statistical issue is labeled *left-truncation*, and the problem is that had the person died before arriving at our door, we would never have known about her. We can add her to our data, but we must be careful to treat her subsequent survival time as conditional on having already survived 15 years.

Say that we are examining visits to the widget repair facility, “failure” being defined as a visit (so failures can be repeated). The risk begins once a person buys a widget. We have a woman who bought a widget 3 years ago, and she has no records on when she has visited the facility in the last 3 years. Can we add her to our data? Yes, as long as we are careful to treat her subsequent behavior as already being 3 years after she first became at risk.

The jargon for this is “under observation”. All this means is that any failures would be observed. Before being under observation, failure would not be observed.

If `enter()` is not specified, we assume that subjects are under observation at the time they enter the risk group as specified by `origin()`, 0 if `origin()` is not specified, or possibly `time0()`. To be precise, subject i is assumed to first enter the analysis risk pool at

$$time_i = \max(\text{earliest } time0() \text{ for } i, \text{enter}(), \text{origin}())$$

Say that we have multiple-record data recording “came at risk” (`mycode == 1`), “enrolled in our study” (`mycode == 2`), and “failed because of risk” (`mycode == 3`). We `stset` this dataset by typing

```
. stset time, id(id) origin(mycode==1) enter(mycode==2) failure(mycode==3)
```

The above `stset` correctly handles the came at risk/came under observation problem regardless of the order of events 1, 2, and 3. For instance, if the subject comes under observation before he or she becomes at risk, the subject will be treated as entering the analysis risk pool at the time he or she came at risk.

Say that we have the same data in single-record format: variable `riskdate` documents becoming at risk and variable `enr_date` the date of enrollment in our study. We would `stset` this dataset by typing

```
. stset time, origin(time riskdate) enter(time enr_date) failure(mycode==3)
```

For a final example, let’s return to the multiple-record way of recording our data and say that we started enrolling people in our study on 12jan1998 but that, up until 16feb1998, we do not trust that our records are complete (we had start-up problems). We would `stset` that dataset by typing

```
. stset time, origin(mycode==1) enter(mycode==2 time mdy(2,16,1998))
> fail(mycode==3)
```

`enter(varname==numlist time exp)` is interpreted as

$$\max(\text{time of earliest event in } numlist, exp)$$

Thus persons having `mycode == 2` occurring before 16feb1998 are assumed to be under observation from 16feb1998, and those having `mycode == 2` thereafter are assumed to be under observation from the time of `mycode == 2`.

Final exit times

`exit()` specifies the latest time under which the subject is both under observation and at risk of the failure event. The emphasis is on latest; obviously subjects also exit the data when their data run out.

When you type

```
. stset ..., ... failure(outcome==1/3 5) ...
```

the result is as if you had typed

```
. stset ..., ... failure(outcome==1/3 5) exit(failure) ...
```

which, in turn, is the same as

```
. stset ..., ... failure(outcome==1/3 5) exit(outcome==1/3 5) ...
```

When are people to be removed from the analysis risk pool? When their data end, of course, and when the event 1, 2, 3, or 5 first occurs. How are they to be removed? According to their status at that time. If the event is 1, 2, 3, or 5 at that instant, they exit as a failure. If the event is something else, they exit as censored.

Perhaps events 1, 2, 3, and 5 represent death due to heart disease, and that is what we are studying. Say that `outcome == 99` represents death for some other reason. Obviously, once the person dies, she is no longer at risk of dying from heart disease, so we would want to specify

```
. stset ..., ... failure(outcome==1/3 5) exit(outcome==1/3 5 99) ...
```

When we explicitly specify `exit()`, we must list all the reasons for which a person is to be removed other than simply running out of data. Here it would have been a mistake to specify just `exit(99)` because that would have left persons in the analysis risk pool who died for reasons 1, 2, 3, and 5. We would have treated those people as if they were still at risk of dying.

In fact, it probably would not have mattered had we specified `exit(99)` because, once a person is dead, he or she is unlikely to have any subsequent records anyway. By that logic, we did not even have to specify `exit(99)` because death is death and there should be no records following it.

For other kinds of events, however, `exit()` becomes important. Let's assume that the failure event is to be diagnosed with heart disease. A person may surely have records following diagnosis, but even so,

```
. stset ..., ... failure(outcome==22) ...
```

would be adequate because, by not specifying `exit()`, we are accepting the default that `exit()` is equivalent to `failure()`. Once outcome 22 occurs, subsequent records on the subject will be ignored—they constitute the future history of the subject.

Say, however, that we wish to treat as censored persons diagnosed with kidney disease. We would type

```
. stset ..., ... failure(outcome==22) exit(outcome==22 29) ...
```

assuming that `outcome = 29` is “diagnosed with kidney disease”. It is now of great importance that we specified `exit(outcome==22 29)` and not just `exit(outcome==29)` because, had we omitted code 22, persons would have remained in the analysis risk pool even after the failure event, that is, being diagnosed with heart disease.

If, in addition, our data were untrustworthy after 22nov1998 (perhaps not all the data have been entered yet), we would type

```
. stset ..., ... failure(outcome==22) exit(outcome==22 29 time
> mdy(11,22,1998)) ...
```

If we type `exit(varname==numlist time exp)`, the exit time is taken to be

$$\min(\text{time of earliest event in } numlist, exp)$$

For some analyses, repeated failures are possible. If you have repeated failure data, you specify the `exit()` option and include whatever reasons, if any, that would cause the person to be removed. If there are no such reasons and you wish to retain all observations for the person, you type

```
. stset ..., ... exit(time .) ...
```

`exit(time .)` specifies that the maximum time a person can be in the risk pool is infinite; thus subjects will not be removed until their data run out.

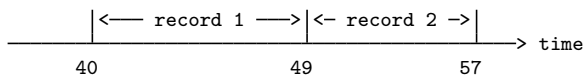
Intermediate exit and reentry times (gaps)

Gaps arise when a subject is temporarily not under observation. The statistical importance of gaps is that, if failure is death and if the person died during such a gap, he would not have been around to be found again. The solution to this is to remove the person from the risk pool during the observational gap.

To determine that you have gaps, your data must provide starting and ending times for each record. Most datasets provide only ending times, making it impossible to know that you have gaps.

You use `time0()` to specify the beginning times of records. `time0()` specifies a mechanical aspect of interpreting the records in the dataset, namely, the beginning of the period spanned by each record. Do not confuse `time0()` with `origin()`, which specifies when a subject became at risk, or with `enter()`, which specifies when a subject first comes under observation.

`time0()` merely identifies the beginning of the time span covered by each record. Say that we had two records on a subject, the first covering the span (40,49] and the second, (49,57]:



A `time0()` variable would contain

```
40 in record 1
49 in record 2
```

and not, for instance, 40 and 40. A `time0()` variable varies record by record for a subject.

Most datasets merely provide an end-of-record time value, *timevar*, which you specify by typing `stset timevar, ...`. When you have multiple records per subject and you do not specify a `time0()` variable, `stset` assumes that each record begins where the previous one left off.

if() versus if exp

Both the `if exp` qualifier and the `if(exp)` option select records for which *exp* is true. We strongly recommend specifying the `if()` option in preference to the `if exp` qualifier. They differ in that the `if exp` qualifier removes data from consideration before calculating beginning and ending times and other quantities as well. The `if()` option, on the other hand, sets the restriction after all derived variables are calculated. To appreciate this difference, consider the following multiple-record data:

patno	t	x1	x2	code
3	7	20	5	14
3	9	22	5	23
3	11	21	5	29

Consider the difference in results between typing

```
. stset t if x1!=22, failure(code==14)
```

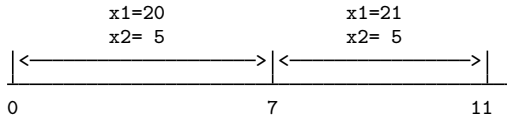
and

```
. stset t, if(x1!=22) failure(code==14)
```

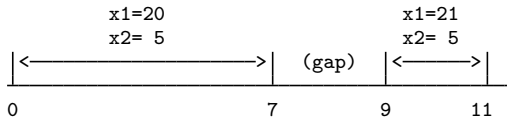
The first would remove record 2 from consideration at the outset. In constructing beginning and ending times, `stset` and `streset` would see

patno	t	x1	x2	code
3	7	20	5	14
3	11	21	5	29

and would construct the result:



In the second case, the result would be



The latter result is correct and the former incorrect because $x1 = 21$ is not true in the interval $(7, 9)$.

The only reason to specify the `if exp` qualifier is to ignore errors in the data—observations that would confuse `stset` and `streset`—without actually dropping the offending observations from the dataset.

You specify the `if()` option to exclude observations that are not themselves errors. Specifying `if()` yields the same result as specifying `if exp` on the subsequent `st` commands after the dataset has been `stset`.

Past and future records

Consider the hospital ward data that we have seen before:

patid	addate	curdate	sex	x1	x2	code
101	18aug1998	23aug1998	1	10	10	177
101	.	31aug1998	1	20	8	286
101	.	08sep1998	1	16	11	208
101	.	11sep1998	1	11	17	401

etc.

Say that you `stset` this dataset such that you selected the middle two records. Perhaps you typed

```
. stset curdate, id(patid) origin(time addate) enter(code==286) failure(code==208)
```

The first record for the subject, because it was not selected, is called a *past history record*. Any earlier records that were not selected would also be called past history records.

The last record for the subject, because it was not selected, is called a *future history record*. Any later records that were not selected would also be called future history records.

If you typed

```
. streset, past
```

the first three records for this subject would be selected.

Typing

```
. streset, future
```

would select the last three records for this subject.

If you typed

```
. streset, past future
```

all four records for this subject would be selected.

If you then typed

```
. streset
```

the original two records would be selected, and things would be back just as they were before.

After typing `streset, past`; `streset, future`; or `streset, past future`, you would not want to use any analysis commands. `streset` did some strange things, especially with the analysis-time variable, to include the extra records. It would be the wrong sample, anyway.

You might, however, want to use certain data management commands on the data, especially those for creating new variables.

Typically, `streset, past` is of greater interest than the other commands. Past records—records prior to being at risk or excluded for other reasons—are not supposed to play a role in survival analysis. `stset` makes sure they do not. But it is sometimes reasonable to ask questions about them such as, was the subject ever on the drug cisplatin? Has the subject ever been married? Did the subject ever have a heart attack?

To answer questions like that, you sometimes want to dig into the past. Typing `streset, past` makes that easy, and once the past is set, the data can be used with `stgen` and `st_is 2`. You might well type the following:

```
. stset curdate, id(patid) origin(addate) enter(code==286) failure(code==208)
. streset, past
. stgen attack = ever(code==177)
. streset
. stcox attack ...
```

Do not be concerned about doing something inappropriate while having the past or future set; `st` will not let you:

```
. stset curdate, id(patid) origin(time addate) enter(code==286) failure(code==208)
  (output omitted)
. streset, past
  (output omitted)
. stcox x1
you last streset, past
you must type streset to restore the analysis sample
r(119);
```

Using `streset`

`streset` is a useful tool for gently modifying what you have previously `stset`. Rather than typing the whole `stset` command, you can type `streset` followed just by what has changed.

For instance, you might type

```
. stset curdate, id(patid) origin(time addate) enter(code==286) failure(code==208)
```

and then later want to restrict the analysis to subjects who ever have $x1 > 20$. You could retype the whole `stset` command and add `ever(x1 > 20)`, but it would be easier to type

```
. streset, ever(x1 > 20)
```

If later you decide you want to remove the restriction, type

```
. streset, ever(.)
```

That is the general rule for resetting options to the default: type `.` as the option's argument.

Be careful using `streset` because you can make subtle mistakes. In another analysis with another dataset, consider the following:

```
. stset date, fail(code==2) origin(code==1107)
. ...
. streset date, fail(code==9) origin(code==1422) after(code==1423)
. ...
. streset, fail(code==2) origin(code==1107)
```

If, in the last step, you are trying to get back to the results of the first `stset`, you will fail. The last `streset` is equivalent to

```
. stset date, fail(code==9) origin(code==1107) after(code==1423)
```

`streset()` remembers the previously specified options and uses them if you do not override them. Both `stset` and `streset` display the current command line. Make sure that you verify that the command is what you intended.

Performance and multiple-record-per-subject datasets

`stset` and `streset` do not drop data; they simply mark data to be excluded from consideration. Some survival-time datasets can be large, although the relevant subsamples are small. In such cases, you can reduce memory requirements and speed execution by dropping the irrelevant observations.

`stset` and `streset` mark the relevant observations by creating a variable named `_st` (it is always named this) containing 1 and 0; `_st = 1` marks the relevant observations and `_st = 0` marks the irrelevant ones. If you type

```
. drop if _st==0
```

or equivalently

```
. keep if _st==1
```

or equivalently

```
. keep if _st
```

you will drop the irrelevant observations. All `st` commands produce the same results whether you do this or not. Be careful, however, if you are planning future `stsets` or `stresets`. Observations that are irrelevant right now might be relevant later.

One solution to this conundrum is to keep only those observations that are relevant after setting the entire history:

```
. stset date, fail(code==9) origin(code==1422) after(code==1423)
. streset, past future
. keep if _st
. streset
```

As a final note, you may drop the irrelevant observations as marked by `_st = 0`, but do not drop the `_st` variable itself. The other `st` commands expect to find variable `_st`.

Sequencing of events within t

Consider the following bit of data:

etime	failtime	fail
0	5	1
0	5	0
5	7	1

Note all the different events happening at time 5: the first observation fails, the second is censored, and the third enters.

What does it mean for something to happen at time 5? In particular, is it at least potentially possible for the second observation to have failed at time 5; that is, was it in the risk group when the first observation failed? How about the third observation? Was it in the risk group, and could it have potentially failed at time 5?

Stata sequences events within a time as follows:

first,	at time t	the failures occur
then,	at time $t + 0$	the censorings are removed from the risk group
finally,	at time $t + 0 + 0$	the new entries are added to the risk group

Thus, to answer the questions:

Could the second observation have potentially failed at time 5? Yes.

Could the third observation have potentially failed at time 5? No, because it was not yet in the risk group.

By this logic, the following makes no sense:

etime	failtime	fail
5	5	1

This would mark a subject as failing before being at risk. It would make no difference if `fail` were 0—the subject would then be marked as being censored too soon. Either way, `stset` would flag this as an error. If you had a subject who entered and immediately exited, you would code this as

etime	failtime	fail
4.99	5	1

Weights

`stset` allows you to specify `fweights`, `pweights`, and `iweights`.

`fweights` are Stata's frequency or replication weights. Consider the data

failtime	load	bearings	count
100	15	0	3
140	15	1	2
97	20	0	1

and the `stset` command

```
. stset failtime [fw=count]
Survival-time data settings
    Failure event: (assumed to fail at time=failtime)
Observed time interval: (0, failtime]
    Exit on or before: failure
    Weight: [fweight=count]
```

```
3 total observations
0 exclusions
```

```
3 physical observations remaining, equal to
6 weighted observations, representing
6 failures in single-record/single-failure data
677 total analysis time at risk and under observation
                                     At risk from t =      0
Earliest observed entry t =          0
Last observed exit t =                140
```

This combination is equivalent to the expanded data

failtime	load	bearings
100	15	0
100	15	0
100	15	0
140	15	1
140	15	1
97	20	0

and the command

```
. stset failtime
```

`pweights` are Stata's sampling weights—the inverse of the probability that the subject was chosen from the population. `pweights` are typically integers, but they do not have to be. For instance, you might have

time0	time	died	sex	reps
0	300	1	0	1.50
0	250	0	1	4.50
30	147	1	0	2.25

Here `reps` is how many patients each observation represents in the underlying population—perhaps when multiplied by 10. The `stset` command for these data is

```
. stset time [pw=reps], origin(time time0) failure(died)
```

For variance calculations, the scale of the `pweights` does not matter. `reps` in the 3 observations shown could just as well be 3, 9, and 4.5. Nevertheless, the scale of the `pweights` is used when you ask for counts. For instance, `stsum` would report the person-time at risk as

$$(300 - 0) 1.5 + (250 - 0) 4.5 + (147 - 30) 2.25 = 1,838.25$$

for the 3 observations shown. `stsum` would count that $1.5 + 2.25 = 3.75$ persons died, and so the incidence rate for these 3 observations would be $3.75/1,838.25 = 0.0020$. The incidence rate is thus unaffected by the scale of the weights. Similarly, the coefficients and confidence intervals reported by, for instance, `streg, dist(exponential)` would be unaffected. The 95% confidence interval for the incidence rate would be $[0.0003, 0.0132]$, regardless of the scale of the weights.

If these 3 observations were examined unweighted, the incidence rate would be 0.0030 and the 95% confidence interval would be [0.0007, 0.0120].

Finally, `stset` allows you to set `iweights`, which are Stata's "importance" weights, but we recommend that you do not. `iweights` are provided for those who wish to create special effects by manipulating standard formulas. The `st` commands treat `iweights` just as they would `fweights`, although they do not require that the weights be integers, and push their way through conventional variance calculations. Thus results—counts, rates, and variances—depend on the scale of these weights.

Data warnings and errors flagged by `stset`

When you `stset` your data, `stset` runs various checks to verify that what you are setting makes sense. `stset` refuses to set the data only if, in multiple-record, weighted data, weights are not constant within `ID`. Otherwise, `stset` merely warns you about any inconsistencies that it identifies.

Although `stset` will set the data, it will mark out records that it cannot understand; for instance,

```
. stset curdate, origin(time addate) failure(code==402) id(patid)
      ID variable: patid
      Failure event: code==402
Observed time interval: (curdate[_n-1], curdate]
Exit on or before: failure
Time for analysis: (time-origin)
      Origin: time addate
```

243	total observations	
1	event time missing (curdate>=.)	PROBABLE ERROR
4	multiple records at same instant (curdate[_n-1]==curdate)	PROBABLE ERROR

238	observations remaining, representing	
40	subjects	
15	failures in single failure-per-subject data	
1,478	total analysis time at risk and under observation	
	At risk from t =	0
	Earliest observed entry t =	0
	Last observed exit t =	62

You must ensure that the result, after exclusions, is correct.

The warnings `stset` might issue include

```
ignored because patid missing
event time missing PROBABLE ERROR
entry time missing PROBABLE ERROR
entry on or after exit (etime>t) PROBABLE ERROR
observations end on or before enter()
observations end on or before origin()
multiple records at same instant (t[_n-1]==t) PROBABLE ERROR
overlapping records (t[_n-1]>entry time) PROBABLE ERROR
weights invalid PROBABLE ERROR
```

`stset` sets `_st = 0` when observations are excluded for whatever reason. Thus observations with any of the above problems can be found among the `_st = 0` observations.

Using survival-time data in Stata

In the examples above, we have shown you how Stata expects survival-time data to be recorded. To summarize:

- Each subject’s history is represented by 1 or more observations in the dataset.
- Each observation documents a span of time. The observation must contain when the span ends (exit time) and may optionally contain when the span begins (entry time). If the entry time is not recorded, it is assumed to be 0 or, in multiple-record data, the exit time of the subject’s previous observation, if there is one. By *previous*, we mean that the data have already been temporally ordered on exit times within subject. The physical order of the observations in your dataset does not matter.
- Each observation documents an outcome associated with the exit time. Unless otherwise specified with `failure()`, 0 and missing mean censored, and nonzero means failed.
- Each observation contains other variables (called covariates) that are assumed to be constant over the span of time recorded by the observation.

Data rarely arrive in this neatly organized form. For instance, [Kalbfleisch and Prentice \(2002, 4–5\)](#) present heart transplant survival data from Stanford ([Crowley and Hu 1977](#)). These data can be converted into the correct st format in at least two ways. The first method is shown in [example 11](#). A second, shorter, method using the st commands is described in [example 3](#) of [\[ST\] stsplit](#).

► Example 11

Here we will describe the process that uses the standard Stata commands.

```
. use https://www.stata-press.com/data/r18/stan2, clear
(Heart transplant data)

. describe
```

```
Contains data from https://www.stata-press.com/data/r18/stan2.dta
Observations:      103           Heart transplant data
Variables:         5             30 Nov 2022 11:14
```

Variable name	Storage type	Display format	Value label	Variable label
id	int	%8.0g		Patient identifier
died	byte	%8.0g		Survival status (1=dead)
stime	float	%8.0g		Survival time (days)
transplant	byte	%8.0g		Heart transplant
wait	int	%8.0g		Waiting time

Sorted by:

The data are from 103 patients selected as transplantation candidates. There is one record on each patient, and the important variables, from an st-command perspective, are

id	the patient’s ID number
transplant	whether the patient received a transplant
wait	when (after acceptance) the patient received the transplant
stime	when (after acceptance) the patient died or was censored
died	the patient’s status at stime

To better understand, let's examine two records from this dataset:

```
. list id transplant wait stime died if id==44 | id==16
```

	id	transp~t	wait	stime	died
33.	44	0	0	40	1
71.	16	1	28	308	1

Patient 44 never did receive a new heart; he or she died 40 days after acceptance while still on the waiting list. Patient 16 did receive a new heart—28 days after acceptance—yet died 308 days after acceptance.

Our goal is to turn this into st data that contain the histories of each of these patients. That is, we want records that appear as

id	t1	died	posttran
16	28	0	0
16	308	1	1
44	40	1	0

or, even more explicitly, as

id	t0	t1	died	posttran
16	0	28	0	0
16	28	308	1	1
44	0	40	1	0

The new variable, `posttran`, would be 0 before transplantation and 1 afterward.

Patient 44 would have one record in this new dataset recording that he or she died at time 40 and that `posttran` was 0 over the entire interval.

Patient 16, however, would have two records: one documenting the duration $(0, 28]$, during which `posttran` was 0, and one documenting the duration $(28, 308]$, during which `posttran` was 1.

Our goal is to take the first dataset and convert it into the second, which we can then `stset`. We make the transformation by using Stata's other data management commands. One way we could do this is by typing

```
. expand 2 if transplant
(69 observations created)
. by id, sort: gen byte posttran = (_n==2)
. by id: gen t1 = stime if _n==_N
(69 missing values generated)
. by id: replace t1 = wait if _n==1 & transplant
(69 real changes made)
. by id: replace died=0 if _n==1 & transplant
(45 real changes made)
```

`expand 2 if transplant` duplicated the observations for patients who had `transplant` $\neq 0$. Considering our two sample patients, we would now have the following data:

id	transp~t	wait	stime	died
44	0	0	40	1
16	1	28	308	1
16	1	28	308	1

We would have 1 observation for patient 44 and 2 identical observations for patient 16.

We then by id, sort: `gen posttran = (_n==2)`, resulting in

id	transp~t	wait	stime	died	posttran
16	1	28	308	1	0
16	1	28	308	1	1
44	0	0	40	1	0

This type of trickiness is discussed in [U] 13.7 **Explicit subscripting**. Statements such as `_n==2` produce values 1 (meaning true) and 0 (meaning false), so new variable `posttran` will contain 1 or 0 depending on whether `_n` is or is not 2. `_n` is the observation counter and, combined with `ID variable:`, becomes the observation-within-ID counter. Thus we set `posttran` to 1 on second records and to 0 on all first records.

Finally, we produce the exit-time variable. Final exit time is just `stime`, and that is handled by the command by id: `gen t1 = stime if _n==_N`. `_n` is the observation-within-ID counter and `_N` is the total number of observations within `id`, so we just set the last observation on each patient to `stime`. Now we have

id	transp~t	wait	stime	died	posttran	t1
16	1	28	308	1	0	.
16	1	28	308	1	1	308
44	0	0	40	1	0	40

All that is left to do is to fill in `t1` with the value from `wait` on the interim records, meaning `replace t1=wait if it is an interim record`.

There are many ways we could identify the interim records. In the output above, we did it by

```
. by id: replace t1 = wait if _n==1 & transplant
```

meaning that an interim record is a first record of a person who did receive a transplant. More easily, but with more trickery, we could have just said

```
. replace t1=wait if t1>=.
```

because the only values of `t1` left to be filled in are the missing ones. Another alternative would be

```
. by id: replace t1 = wait if _n==1 & _N==2
```

which would identify the first record of two-record pairs. There are many alternatives, but they would all produce the same thing:

id	transp~t	wait	stime	died	posttran	t1
16	1	28	308	1	0	28
16	1	28	308	1	1	308
44	0	0	40	1	0	40

There is one more thing we must do, which is to reset `died` to contain 0 on the interim records:

```
. by id: replace died=0 if _n==1 & transplant
```

The result is

id	transp~t	wait	stime	died	posttran	t1
16	1	28	308	0	0	28
16	1	28	308	1	1	308
44	0	0	40	1	0	40

We now have the desired result and are ready to `stset` our data:

```
. stset t1, failure(died) id(id)
Survival-time data settings
      ID variable: id
      Failure event: died!=0 & died<.
Observed time interval: (t1[_n-1], t1]
      Exit on or before: failure
```

```
172 total observations
   2 multiple records at same instant          PROBABLE ERROR
      (t1[_n-1]==t1)
```

```
170 observations remaining, representing
102 subjects
  74 failures in single-failure-per-subject data
31,933 total analysis time at risk and under observation
              At risk from t =           0
      Earliest observed entry t =           0
              Last observed exit t =       1,799
```

Well, something went wrong. Two records were excluded. There are few enough data here that we could just list the dataset and look for the problem, but let's pretend otherwise. We want to find the records that, within patient, are marked as exiting at the same time:

```
. by id: gen problem = t1==t1[_n-1]
. sort id died
. list id if problem
```

	id
61.	38

```
. list id transplant wait stime died posttran t1 if id==38
```

	id	transp ^t	wait	stime	died	posttran	t1
60.	38	1	5	5	0	0	5
61.	38	1	5	5	1	1	5

There is no typographical error in these data—we checked that variables `transplant`, `wait`, and `stime` contain what the original source published. Those variables indicate that patient 38 waited 5 days for a heart transplant, received one on the fifth day, and then died on the fifth day, too.

That makes perfect sense, but not to Stata, which orders events within t as failures, followed by censorings, followed by entries. Reading `t1`, Stata went for this literal interpretation: patient 38 was censored at time 5 with `posttran = 0`; then, at time 5, patient 38 died; and then, at time 5, patient 38 reentered the data, but this time with `posttran = 1`. That made no sense to Stata.

Stata's sequencing of events may surprise you, but trust us, there are good reasons for it, and really, the ordering convention does not matter. To fix this problem, we just have to put a little time between the implied entry at time 5 and the subsequent death:

```
. replace t1 = 5.1 in 61
(1 real change made)
. list id transplant wait stime died posttran t1 if id==38
```

	id	transp~t	wait	stime	died	posttran	t1
60.	38	1	5	5	0	0	5
61.	38	1	5	5	1	1	5.1

Now the data make sense both to us and to Stata: until time 5, the patient had `posttran = 0`; then, at time 5, the value of `posttran` changed to 1; and then, at time 5.1, the patient died.

```
. stset t1, id(id) failure(died)
Survival-time data settings
      ID variable: id
      Failure event: died!=0 & died<.
Observed time interval: (t1[_n-1], t1]
Exit on or before: failure
```

```
172 total observations
  0 exclusions
```

```
172 observations remaining, representing
103 subjects
 75 failures in single-failure-per-subject data
31,938.1 total analysis time at risk and under observation
                At risk from t =          0
Earliest observed entry t =          0
                Last observed exit t =    1,799
```

This dataset is now ready for use with all the other `st` commands. Here is an illustration:

```
. use https://www.stata-press.com/data/r18/stan3, clear
(Heart transplant data)
. stset, noshow
. stsum, by(posttran)
```

posttran	Time at risk	Incidence rate	Number of subjects	Survival time		
				25%	50%	75%
0	5,936	.0050539	103	36	149	340
1	26,002.1	.0017306	69	39	96	979
Total	31,938.1	.0023483	103	36	100	979

```

. stcox age posttran surgery year
Iteration 0:  Log likelihood = -298.31514
Iteration 1:  Log likelihood = -289.7344
Iteration 2:  Log likelihood = -289.53498
Iteration 3:  Log likelihood = -289.53378
Iteration 4:  Log likelihood = -289.53378
Refining estimates:
Iteration 0:  Log likelihood = -289.53378
Cox regression with Breslow method for ties
No. of subjects =      103                Number of obs =      172
No. of failures =       75
Time at risk    = 31,938.1
Log likelihood = -289.53378                LR chi2(4)    =   17.56
                                           Prob > chi2   =   0.0015

```

_t	Haz. ratio	Std. err.	z	P> z	[95% conf. interval]	
age	1.030224	.0143201	2.14	0.032	1.002536	1.058677
posttran	.9787243	.3032597	-0.07	0.945	.5332291	1.796416
surgery	.3738278	.163204	-2.25	0.024	.1588759	.8796
year	.8873107	.059808	-1.77	0.076	.7775022	1.012628

◀

Video example

[Learn how to set up your data for survival analysis](#)

References

- Cleves, M. A., W. W. Gould, and Y. V. Marchenko. 2016. *An Introduction to Survival Analysis Using Stata*. Rev. 3rd ed. College Station, TX: Stata Press.
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- Kalbfleisch, J. D., and R. L. Prentice. 2002. *The Statistical Analysis of Failure Time Data*. 2nd ed. New York: Wiley.

Also see

[ST] [snapspan](#) — Convert snapshot data to time-span data

[ST] [stdescribe](#) — Describe survival-time data

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