stbase — Form baseline dataset

Description

`stbase` without the `at()` option converts multiple-record st data to st data with every variable set to its value at baseline, defined as the earliest time at which each subject was observed. `stbase` without `at()` does nothing to single-record st data.

`stbase, at()` converts single- or multiple-record st data to a cross-sectional dataset (not st data), recording the number of failures at the specified time. All variables are given their values at baseline—the earliest time at which each subject was observed. In this form, single-failure data could be analyzed by logistic regression and multiple-failure data by Poisson regression, for instance.

`stbase` can be used with single- or multiple-record or single- or multiple-failure st data.

Quick start

Set all variables to their values at the earliest time the subject was observed using `stset` data

```
stbase
```

Create a dataset with one observation per subject, recording number of failures at time 10, with all variables set to the value at the earliest time the subject was observed

```
stbase, at(10)
```

Menu

Statistics > Survival analysis > Setup and utilities > Form baseline dataset

Syntax

`stbase` [*if*] [*in*] [, *options*]

options	Description
Main	
`at(#)`	convert single/multiple-record st data to cross-sectional dataset at time #
`gap(`*newvar*`)`	name of variable containing gap time; default is `gap` or `gaptime`
`replace`	overwrite current data in memory
`noshow`	do not show st setting information
`nopreserve`	programmer's option; see *Options* below

You must `stset` your data before using `stbase`; see [ST] **stset**.
`fweight`s, `iweight`s, and `pweight`s may be specified using `stset`; see [ST] **stset**.
`nopreserve` does not appear in the dialog box.

Options

Main

`at(#)` changes what `stbase` does. Without the `at()` option, `stbase` produces another related st dataset. With the `at()` option, `stbase` produces a related cross-sectional dataset.

`gap(`*newvar*`)` is allowed only with `at()`; it specifies the name of a new variable to be added to the data containing the amount of time the subject was not at risk after entering and before # as specified in `at()`. If `gap()` is not specified, the new variable will be named `gap` or `gaptime`, depending on which name does not already exist in the data.

`replace` specifies that it is okay to change the data in memory, even though the dataset has not been saved to disk in its current form.

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

The following option is available with `stbase` but is not shown in the dialog box:

`nopreserve` is for use by programmers using `stbase` as a subroutine. It specifies that `stbase` not preserve the original dataset so that it can be restored should an error be detected or should the user press *Break*. Programmers would specify this option if, in their program, they had already preserved the original data.

Remarks and examples

Remarks are presented under the following headings:

stbase without the at() option

Once you type stbase, you may not streset your data, even though the data are st. streset will refuse to run because the data have changed, and if the original rules were reapplied, they might produce different, incorrect results. The st commands use four key variables:

_t0	the time at which the record came under observation
_t	the time at which the record left observation
_d	1 if the record left under failure, 0 otherwise
_st	whether the observation is to be used (contains 1 or 0)

These variables are adjusted by stbase. The _t0 and _t variables, in particular, are derived from your variables according to options you specified at the time you stset the data, which might include an origin() rule, an entry() rule, and the like. Once intervening observations are eliminated, those rules will not necessarily produce the same results that they did previously.

To illustrate how stbase works, consider multiple-record, time-varying st data, on which you have performed some analysis. You now wish to compare your results with a simpler, non-time-varying analysis. For instance, suppose that variables x1 and x2 measure blood pressure and weight, respectively, and that readings were taken at various times. Perhaps you fit the model

```
. use https://www.stata-press.com/data/r19/mfail

. stset
-> stset t, id(id) failure(d) exit(time .) noshow

Survival-time data settings

           ID variable: id
         Failure event: d!=0 & d<.
Observed time interval: (t[_n-1], t]
     Exit on or before: time .
--------------------------------------------------------------------------
      1,734  total observations
          0  exclusions
--------------------------------------------------------------------------
      1,734  observations remaining, representing
        926  subjects
        808  failures in multiple-failure-per-subject data
    435,855  total analysis time at risk and under observation
                                                At risk from t =         0
                                     Earliest observed entry t =         0
                                          Last observed exit t =       960
```

```
. stcox x1 x2

Iteration 0:  Log likelihood = -5034.9569
Iteration 1:  Log likelihood = -4978.4198
Iteration 2:  Log likelihood = -4978.1915
Iteration 3:  Log likelihood = -4978.1914
Refining estimates:
Iteration 0:  Log likelihood = -4978.1914

Cox regression with Breslow method for ties

No. of subjects =     926                           Number of obs =  1,734
No. of failures =     808
Time at risk    = 435,855
                                                    LR chi2(2)    = 113.53
Log likelihood = -4978.1914                         Prob > chi2   = 0.0000

------------------------------------------------------------------------------
          _t | Haz. ratio   Std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
          x1 |   2.273456    .216537     8.62   0.000     1.886311    2.740059
          x2 |    .329011   .0685638    -5.33   0.000     .2186883    .4949888
------------------------------------------------------------------------------
```

with these data. You now wish to fit that same model but this time use the values of x1 and x2 at baseline. You do this by typing

```
. stbase, replace

Converting multiple-record data to baseline data ...

Notes:
    1. No gaps.
    2. There were multiple failures or reentries after failures.
    3. Baseline data have multiple records per ID (id).
    4. All records have covariate values at baseline.

. stcox x1 x2

Iteration 0:  Log likelihood = -7886.9779
Iteration 1:  Log likelihood = -7863.9974
Iteration 2:  Log likelihood = -7863.9295
Iteration 3:  Log likelihood = -7863.9295
Refining estimates:
Iteration 0:  Log likelihood = -7863.9295

Cox regression with Breslow method for ties

No. of subjects =     926                           Number of obs =  1,734
No. of failures =   1,337
Time at risk    = 435,855
                                                    LR chi2(2)    =  46.10
Log likelihood = -7863.9295                         Prob > chi2   = 0.0000

------------------------------------------------------------------------------
          _t | Haz. ratio   Std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
          x1 |   1.413195   .1107945     4.41   0.000     1.211903    1.647921
          x2 |   .4566673   .0765272    -4.68   0.000     .3288196    .6342233
------------------------------------------------------------------------------
```

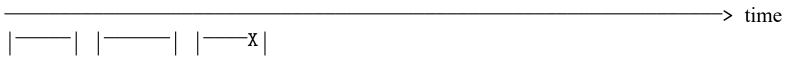
Another way you could perform the analysis is to type

```
. generate x1_0 = x1

. generate x2_0 = x2

. stfill x1_0 x2_0, baseline

. stcox x1 x2
```

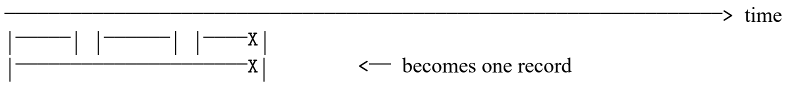
See [ST] **stfill**. The method you use makes no difference, but if there were many explanatory variables, `stbase` would be easier.

`stbase` changes the data to record the same events but changes the values of all other variables to their values at the earliest time the subject was observed.

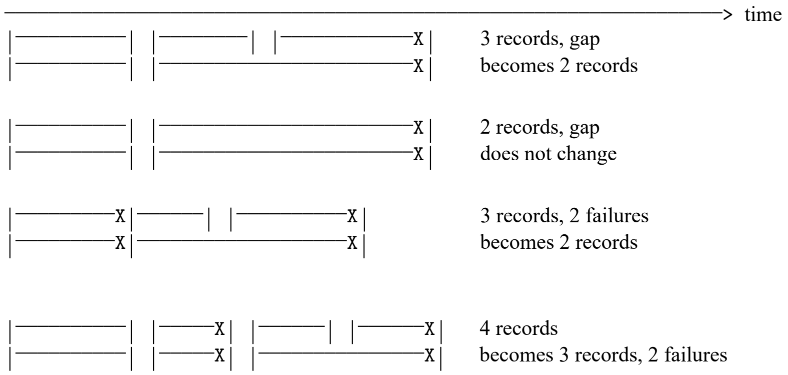
`stbase` also simplifies the st data where possible. Say that one of your subjects has three records in the original data and ends in a failure:



After running `stbase`, this subject would have one record in the data:



Here are some other examples of how `stbase` would process records with gaps and multiple failure events:



The following example shows numerically what is shown in the diagram above.

```
. use https://www.stata-press.com/data/r19/stbasexmpl, clear
. list, sepby(id)

     +-----------------------------------+
     | id   time0   time   wgt   death   |
     |-----------------------------------|
  1. |  1       0      2   114       0   |
  2. |  1       3      5   110       0   |
  3. |  1       5     11   118       1   |
     |-----------------------------------|
  4. |  2       0      2   120       0   |
  5. |  2       3     11   111       1   |
     |-----------------------------------|
  6. |  3       0      2   108       1   |
  7. |  3       2      4   105       0   |
  8. |  3       4      7   113       1   |
     |-----------------------------------|
  9. |  4       0      2    98       0   |
 10. |  4       3      4   101       1   |
 11. |  4       5      6   106       0   |
 12. |  4       6     11   104       1   |
     +-----------------------------------+
. stset time, id(id) fail(death) time0(time0) exit(time .)
Survival-time data settings
           ID variable: id
         Failure event: death!=0 & death<.
Observed time interval: (time0, time]
     Exit on or before: time .
──────────────────────────────────────────────────────────────────────────
         12  total observations
          0  exclusions
──────────────────────────────────────────────────────────────────────────
         12  observations remaining, representing
          4  subjects
          6  failures in multiple-failure-per-subject data
         36  total analysis time at risk and under observation
                                                At risk from t =         0
                                     Earliest observed entry t =         0
                                          Last observed exit t =        11

. list, sepby(id)

     ┌────────────────────────────────────────────────────────┐
     │ id   time0   time   wgt   death   _st   _d   _t   _t0 │
     ├────────────────────────────────────────────────────────┤
  1. │  1       0      2   114       0     1    0    2     0 │
  2. │  1       3      5   110       0     1    0    5     3 │
  3. │  1       5     11   118       1     1    1   11     5 │
     ├────────────────────────────────────────────────────────┤
  4. │  2       0      2   120       0     1    0    2     0 │
  5. │  2       3     11   111       1     1    1   11     3 │
     ├────────────────────────────────────────────────────────┤
  6. │  3       0      2   108       1     1    1    2     0 │
  7. │  3       2      4   105       0     1    0    4     2 │
  8. │  3       4      7   113       1     1    1    7     4 │
     ├────────────────────────────────────────────────────────┤
  9. │  4       0      2    98       0     1    0    2     0 │
 10. │  4       3      4   101       1     1    1    4     3 │
 11. │  4       5      6   106       0     1    0    6     5 │
 12. │  4       6     11   104       1     1    1   11     6 │
     └────────────────────────────────────────────────────────┘

. stbase, replace
         Failure _d: death
   Analysis time _t: time
  Exit on or before: time .
        ID variable: id
Converting multiple-record data to baseline data ...
Notes:
    1. There were gaps.
    2. There were multiple failures or reentries after failures.
    3. Baseline data have multiple records per ID (id).
    4. All records have covariate values at baseline.
```

```
. list, sepby(id)

     ┌──────────────────────────────────────────────────────────────┐
     │ id   time0   time   wgt   death   _st   _d   _t   _t0 │
     ├──────────────────────────────────────────────────────────────┤
  1. │  1       0      2   114       0     1    0    2     0 │
  2. │  1       3     11   114       1     1    1   11     3 │
     ├──────────────────────────────────────────────────────────────┤
  3. │  2       0      2   120       0     1    0    2     0 │
  4. │  2       3     11   120       1     1    1   11     3 │
     ├──────────────────────────────────────────────────────────────┤
  5. │  3       0      2   108       1     1    1    2     0 │
  6. │  3       2      7   108       1     1    1    7     2 │
     ├──────────────────────────────────────────────────────────────┤
  7. │  4       0      2    98       0     1    0    2     0 │
  8. │  4       3      4    98       1     1    1    4     3 │
  9. │  4       5     11    98       1     1    1   11     5 │
     └──────────────────────────────────────────────────────────────┘
```

stbase with the at() option

`stbase, at()` produces a cross-sectional dataset recording the status of each subject at the specified time. This new dataset is not st. Four "new" variables are created:

- the first entry time for the subject,
- the time on gap,
- the time at risk, and
- the number of failures during the time at risk.

The names given to those variables depend on how your data are `stset`. Pretend that your `stset` command was

```
. stset var1, failure(var2) time0(var3) ...
```

Then

the first entry time	will be named	*var3* or `time0` or `_t0`
the time on gap	will be named	`gap()` or `gap` or `gaptime`
the time at risk	will be named	*var1*
the number of (or whether) failures	will be named	*var2* or `failure` or `_d`

The names may vary because, for instance, if you did not specify a *var2* variable when you `stset` your data, `stbase, at()` looks around for a name.

You need not memorize this; the names are obvious from the output produced by `stbase, at()`.

Consider the actions of `stbase, at()` with some particular st datasets. Pretend that the command given is

```
. use https://www.stata-press.com/data/r19/stbasexmpl2, clear
. list, sepby(id)

     +-----------------------------------+
     | id   time0   time   wgt   death   |
     |-----------------------------------|
  1. |  1       0      2   114       0   |
  2. |  1       2      8   110       0   |
  3. |  1       8     11   118       1   |
     |-----------------------------------|
  4. |  2       0      1   120       0   |
  5. |  2       1      3   111       0   |
  6. |  2       3      8   108       0   |
  7. |  2       8     10    98       1   |
     +-----------------------------------+

. stset time, id(id) fail(death) time0(time0)
Survival-time data settings

           ID variable: id
         Failure event: death!=0 & death<.
Observed time interval: (time0, time]
     Exit on or before: failure
--------------------------------------------------------------------------
          7  total observations
          0  exclusions
--------------------------------------------------------------------------
          7  observations remaining, representing
          2  subjects
          2  failures in single-failure-per-subject data
         21  total analysis time at risk and under observation
                                                At risk from t =         0
                                     Earliest observed entry t =         0
                                          Last observed exit t =        11

. list, sepby(id)

     +--------------------------------------------------------+
     | id   time0   time   wgt   death   _st   _d   _t   _t0  |
     |--------------------------------------------------------|
  1. |  1       0      2   114       0     1    0    2     0  |
  2. |  1       2      8   110       0     1    0    8     2  |
  3. |  1       8     11   118       1     1    1   11     8  |
     |--------------------------------------------------------|
  4. |  2       0      1   120       0     1    0    1     0  |
  5. |  2       1      3   111       0     1    0    3     1  |
  6. |  2       3      8   108       0     1    0    8     3  |
  7. |  2       8     10    98       1     1    1   10     8  |
     +--------------------------------------------------------+
. stbase, at(5) replace
        Failure _d: death
  Analysis time _t: time
       ID variable: id
Converting multiple-record data to cross-sectional data ...
Cross-sectional data
  recording each subject status at time 5
    Variable  Description
─────────────────────────────────────────────────────────
          id  Subject identifier
       time0  First entry time
         gap  Time on gap
        time  Time at risk
       death  Number of failures during time at risk
    Variable         Obs        Mean    Std. dev.       Min        Max
─────────────────────────────────────────────────────────────────────
       time0           2           0           0          0          0
         gap           2           0           0          0          0
        time           2           5           0          5          5
       death           2           0           0          0          0
. list

     ┌──────────────────────────────────────────┐
     │ id   wgt   death   time   time0   gap    │
     ├──────────────────────────────────────────┤
  1. │  1   114       0      5       0     0    │
  2. │  2   120       0      5       0     0    │
     └──────────────────────────────────────────┘
```

thus producing a cross-section at analysis time 5.

Note that the value of time specified with the `at()` option must correspond to time in the analysis scale, that is, *t*. See [ST] **stset** for a definition of analysis time.

Single-failure st data where all subjects enter at time 0

The result of `stbase, at(5)` would be one record per subject. Any subject who was censored before time 5 would not appear in the data; the rest would. Those that failed after time 5 will be recorded as having been censored at time 5 (*failvar* = 0); those that failed at time 5 or earlier will have *failvar* = 1.

timevar will contain

for the failures:	
time of failure	if failed on or before time 5 or
5	if the subject has not failed yet
for the censored:	
5	if the subject has not failed yet

With such data, you could perform

- logistic regression of *failvar* on any of the characteristics or
- incidence-rate analysis, summing the failures (perhaps within strata) and the time at risk, *timevar*.

With these data, you could examine 5-year survival probabilities.

Single-failure st data where some subjects enter after time 0

The data produced by `stbase, at(5)` would be similar to the above, except

- persons who enter on or after time 5 would not be included in the data (because they have not entered yet) and
- the time at risk, *timevar*, would properly account for the time at which each patient entered.

timevar (the time at risk) will contain

for the failures:	
time of failure or less	if failed on or before time 5 (or less because the subject may not have entered at time 0); or
5 or less	if the subject has not failed yet (or less because the subject may not have entered at time 0)
for the censored:	
5 or less	if the subject has not failed yet (or less because the subject may not have entered at time 0)

Depending on the analysis you are performing, you may have to discard those that enter late. This is easy to do because `t0` contains the first time of entry.

With these data, you could perform the following:

- Logistic regression of *failvar* on any of the characteristics, but only if you restricted the sample to `if t0==0` because those who entered after time 0 have a lesser risk of failing over the fixed interval.
- Incidence-rate analysis, summing the failures (perhaps within stratum) and the time at risk, *timevar*. Here you would have to do nothing differently from what you did in the previous example. The time-at-risk variable already includes the time of entry for each patient.

Single-failure st data with gaps and perhaps delayed entry

These data will be similar to the delayed-entry, no-gap data, but `gap` will contain 0 only for those observations that have no gap.

If analyzing these data, you could perform

- logistic regression, but the sample must be restricted to `if t0==0 & gap==0`, or
- incidence-rate analysis, and nothing would need to be done differently; the time at risk, *timevar*, accounts for late entry and gaps.

Multiple-failure st data

The multiple-failure case parallels the single-failure case, except that `fail` will not solely contain 0 and 1; it will contain 0, 1, 2, . . . , depending on the number of failures observed. Regardless of late entry, gaps, etc., you could perform

- Poisson regression of `fail`, the number of events, but remember to specify `exposure(`*timevar*`)`, and
- incidence-rate analysis.

Also see

[ST] **stfill** — Fill in by carrying forward values of covariates

[ST] **stset** — Declare data to be survival-time data