Description

`bstat` is a programmer’s command that computes and displays estimation results from bootstrap statistics. For each variable in `varlist`, `bstat` computes a covariance matrix, estimates bias, and constructs normal confidence intervals (CIs), percentile CIs, bias-corrected (BC) CIs, and bias-corrected and accelerated (BCa) CIs using a bootstrap dataset in memory or on disk. The computed CIs can be displayed using `estat bootstrap`; see [R] bootstrap postestimation.

`bstat` without `varlist` replays results from the last bootstrap estimation when results are stored in `e()`.

Menu

Statistics > Resampling > Report bootstrap results
**Syntax**

**Bootstrap statistics from variables**

```
bstat [ varlist ] [ if ] [ in ] [ , options ]
```

**Bootstrap statistics from file**

```
bstat [ namelist ] [ using filename ] [ if ] [ in ] [ , options ]
```

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*Starred options and qualifiers using, if, and in require a bootstrap dataset.

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

**Options**

**Main**

- `stat(vector)` specifies the observed value of each statistic (that is, the value of the statistic using the original dataset).

- `accel(vector)` specifies the acceleration of each statistic, which is used to construct BCa CIs.

- `ties` specifies that `bstat` adjust for ties in the replicate values when computing the median bias used to construct BC and BCa CIs.

- `mse` specifies that `bstat` compute the variance by using deviations of the replicates from the observed value of the statistics. By default, `bstat` computes the variance by using deviations from the average of the replicates.

**Reporting**

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

- `n(#)` specifies the number of observations from which bootstrap samples were taken. This value is used in no calculations but improves the table header when this information is not saved in the bootstrap dataset.
notable suppresses the display of the output table.
noheader suppresses the display of the table header. This option implies nolegend.
nolegend suppresses the display of the table legend.
verbose specifies that the full table legend be displayed. By default, coefficients and standard errors are not displayed.
title(text) specifies a title to be displayed above the table of bootstrap results; the default title is Bootstrap results.
display_options: cformat(%fmt), pformat(%fmt), sformat(%fmt), and nolstretch; see [R] Estimation options.

Remarks and examples

Remarks are presented under the following headings:

Bootstrap datasets
Creating a bootstrap dataset

Bootstrap datasets

Although bstat allows you to specify the observed value and acceleration of each bootstrap statistic via the stat() and accel() options, programmers may be interested in what bstat uses when these options are not supplied.

When working from a bootstrap dataset, bstat first checks the data characteristics (see [P] char) that it understands:

_dta[bs_version] identifies the version of the bootstrap dataset. This characteristic may be empty (not defined), 2, or 3; otherwise, bstat will quit and display an error message. This version tells bstat which other characteristics to look for in the bootstrap dataset.

bstat uses the following characteristics from version 3 bootstrap datasets:

_dta[N]
_dta[N_strata]
_dta[N_cluster]
_dta[command]
varname[observed]
varname[acceleration]
varname[expression]

bstat uses the following characteristics from version 2 bootstrap datasets:

_dta[N]
_dta[N_strata]
_dta[N_cluster]
varname[observed]
varname[acceleration]

An empty bootstrap dataset version implies that the dataset was created by the bstrap command in a version of Stata earlier than Stata 8. Here bstat expects varname[bstrap] to contain the observed value of the statistic identified by varname (varname[observed] in version 2). All other characteristics are ignored.

_dta[N] is the number of observations in the observed dataset. This characteristic may be overruled by specifying the n() option.
_dta[N_strata] is the number of strata in the observed dataset.
_dta[N_cluster] is the number of clusters in the observed dataset.
_dta[command] is the command used to compute the observed values of the statistics.

varname[observed] is the observed value of the statistic identified by varname. To specify a different value, use the stat() option.

varname[acceleration] is the estimate of acceleration for the statistic identified by varname. To specify a different value, use the accel() option.

varname[expression] is the expression or label that describes the statistic identified by varname.

Creating a bootstrap dataset

Suppose that we are interested in obtaining bootstrap statistics by resampling the residuals from a regression (which is not possible with the bootstrap command). After loading some data, we run a regression, save some results relevant to the bstat command, and save the residuals in a new variable, res.

```
use https://www.stata-press.com/data/r16/auto
(1978 Automobile Data)
.regress mpg weight length

Source | SS      | df | MS         | Number of obs = 74
--------|---------|----|------------|-------------------
Model   | 1616.08062 | 2  | 808.040312 | F(2, 71) = 69.34
Residual| 827.378835 | 71 | 11.653223  | Prob > F = 0.0000
        |          |    |            | R-squared = 0.6614
        |          |    |            | Adj R-squared = 0.6519
Total   | 2443.45946 | 73 | 33.4720474 | Root MSE = 3.4137
--------|---------|----|------------|-------------------

mpg     | Coef.   | Std. Err. | t     | P>|t| | [95% Conf. Interval]|
--------|---------|-----------|------|------|---------------------|
weight  | -.0038515 | .001586 | -2.43| 0.018| -.0070138 -.0006891|
length  | -.0795935 | .0553577 | -1.44| 0.155| -.1899736 .0307867|
_cons   | 47.88487  | 6.08787  | 7.87 | 0.000| 35.746 60.02374|
```

```
.matrix b = e(b)
.local n = e(N)
.predict res, residuals
```
We can resample the residual values in `res` by generating a random observation ID (`rid`), generate a new response variable (`y`), and run the original regression with the new response variables.

```
. set seed 54321
. generate rid = int(_N*runiform())+1
. matrix score double y = b
. replace y = y + res[rid]
(74 real changes made)
. regress y weight length
```

```
Source | SS      | df | MS       | Number of obs = 74
--------|---------|----|----------|-------------------
Model   | 1695.70314 | 2  | 847.851568 | F(2, 71) = 100.11
Residual| 601.341031  | 71 | 8.46959199 | Prob > F = 0.0000
        |          |    |          | R-squared = 0.7382
        |          |    |          | Adj R-squared = 0.7308
Total   | 2297.04417 | 73 | 31.4663585 | Root MSE = 2.9103
```

```
y | Coef.  | Std. Err. | t     | P>|t| | [95% Conf. Interval]
---|--------|-----------|------|-----|----------------------
weight| -.0029676 | .0013521 | -2.19 | 0.031 | -.0056636 | -.0002716
length| -.1158425 | .047194 | -2.45 | 0.017 | -.2099446 | -.0217404
_cons  | 51.72451 | 5.190075 | 9.97  | 0.000 | 41.3758 | 62.07323
```

Instead of programming this resampling inside a loop, it is much more convenient to write a short program and use the `simulate` command; see [R] simulate. In the following, `mysim_r` requires the user to specify a coefficient vector and a residual variable. `mysim_r` then retrieves the list of predictor variables (removing `_cons` from the list), generates a new temporary response variable with the resampled residuals, and regresses the new response variable on the predictors.

```
program mysim_r
version 16.1
syntax name(name=bvector), res(varname)
tempvar y rid
local xvars : colnames `bvector'
local cons _cons
local xvars : list xvars - cons
matrix score double `y' = `bvector'
generate long `rid' = int(_N*runiform()) + 1
replace `y' = `y' + `res'[`rid']
replace `res' = `res' - `y'
regress `y' `xvars'
end
```
We can now give `mysim_r` a test run, but we first set the random-number seed (to reproduce results).

```stata
. set seed 54321
. mysim_r b, res(res)
(74 real changes made)

Source | SS       | df | MS       | Number of obs = 74
       |    |    |          | F(2, 71) = 100.11
Model  | 1695.70314 | 2 | 847.851568 | Prob > F = 0.0000
Residual | 601.341031 | 71 | 8.46959199 | R-squared = 0.7382
       | | | | Adj R-squared = 0.7308
Total  | 2297.04417 | 73 | 31.4663585 | Root MSE = 2.9103

| Coef. | Std. Err. | t | P>|t| | [95% Conf. Interval] |
|-------------------------|-----------------|--------|------------|-----------------------|
| _b_weight               | -.0029676       | .0013521 | -2.19      | 0.031                 | -.0056636 -.0002716 |
| _b_length               | -.1158425       | .047194 | -2.45      | 0.017                 | -.2099446 -.0217404 |
| _cons                   | 51.72451        | 5.190075 | 9.97       | 0.000                 | 41.3758 62.07323   |
```

Now that we have a program that will compute the results we want, we can use `simulate` to generate a bootstrap dataset and `bstat` to display the results.

```stata
. set seed 54321
. simulate, reps(200) nodots: mysim_r b, res(res)
 command: mysim_r b, res(res)
 . bstat, stat(b) n('n')

Bootstrap results

| Coef. | Std. Err. | t | P>|t| | [95% Conf. Interval] |
|-------------------------|-----------------|--------|------------|-----------------------|
| _b_weight               | -.0038515       | .0014673 | -2.62      | 0.009                 | -.0067274 -.0009756 |
| _b_length               | -.0795935       | .0509772 | -1.56      | 0.118                 | -.1795069 .0203199  |
| _b_cons                 | 47.88487        | 5.650947 | 8.47       | 0.000                 | 36.80922 58.96053   |
```

Finally, we see that `simulate` created some of the data characteristics recognized by `bstat`. All we need to do is correctly specify the version of the bootstrap dataset, and `bstat` will automatically use the relevant data characteristics.
. char list
_dta[rngstate]: XAA0000000000000d431c5e5401775ee9b9e24b2604d4885..
_dta[command]: mysim_r b, res(res)
_b_weight[is_eexp]: 1
_b_weight[colname]: weight
_b_weight[coleq]: _
_b_weight[expression]: _b[weight]
_b_length[is_eexp]: 1
_b_length[colname]: length
_b_length[coleq]: _
_b_length[expression]: _b[length]
_b_cons[is_eexp]: 1
_b_cons[colname]: _cons
_b_cons[coleq]: _
_b_cons[expression]: _b[_cons]

. char _dta[bs_version] 3
. bstat, stat(b) n('n')

Bootstrap results Number of obs =  74
Replications =  200

command: mysim_r b, res(res)

<table>
<thead>
<tr>
<th></th>
<th>Observed</th>
<th>Bootstrap</th>
<th>Normal-based</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coef.</td>
<td>Std. Err.</td>
<td>z</td>
</tr>
<tr>
<td>weight</td>
<td>-.0038515</td>
<td>.0014673</td>
<td>-2.62</td>
</tr>
<tr>
<td>length</td>
<td>-.0795935</td>
<td>.0509772</td>
<td>-1.56</td>
</tr>
<tr>
<td>_cons</td>
<td>47.88487</td>
<td>5.650947</td>
<td>8.47</td>
</tr>
</tbody>
</table>

See Poi (2004) for another example of residual resampling.
bstat — Report bootstrap results

Stored results

bstat stores the following in e():

Scalars

- e(N) sample size
- e(N_reps) number of complete replications
- e(N_misreps) number of incomplete replications
- e(N_strata) number of strata
- e(N_clust) number of clusters
- e(k_aux) number of auxiliary parameters
- e(k_eq) number of equations in e(b)
- e(k_exp) number of standard expressions
- e(k_exexp) number of extended expressions (i.e., _b)
- e(k_extra) number of extra equations beyond the original ones from e(b)
- e(level) confidence level for bootstrap CIs
- e(bs_version) version for bootstrap results
- e(rank) rank of e(V)

Macros

- e(cmd) bstat
- e(command) from _dta[command]
- e(cmdline) command as typed
- e(title) title in estimation output
- e(exp#) expression for the #th statistic
- e(prefix) bootstrap
- e(ties) ties, if specified
- e(mse) mse, if specified
- e(vce) bootstrap
- e(vcetype) title used to label Std. Err.
- e(properties) b V

Matrices

- e(b) observed statistics
- e(b_bs) bootstrap estimates
- e(reps) number of nonmissing results
- e(bias) estimated biases
- e(se) estimated standard errors
- e(z0) median biases
- e(accel) estimated accelerations
- e(ci_normal) normal-approximation CIs
- e(ci_percentile) percentile CIs
- e(ci_bc) bias-corrected CIs
- e(ci_bca) bias-corrected and accelerated CIs
- e(V) bootstrap variance–covariance matrix

References


Also see

[R] bootstrap postestimation — Postestimation tools for bootstrap
[R] bootstrap — Bootstrap sampling and estimation
[R] bsample — Sampling with replacement