Survey — Introduction to survey commands

Description

The Survey Data Reference Manual is organized alphabetically, making it easy to find an individual entry if you know the name of a command. This overview organizes and presents the commands conceptually, that is, according to the similarities in the functions they perform.

Survey design tools

[SVY] svyset Declare survey design for dataset
[SVY] svydescribe Describe survey data

Survey data analysis tools

[SVY] svy The survey prefix command
[SVY] svy estimation Estimation commands for survey data
[SVY] svy: tabulate oneway One-way tables for survey data
[SVY] svy: tabulate twoway Two-way tables for survey data
[SVY] svy postestimation Postestimation tools for svy
[SVY] estat Postestimation statistics for survey data, such as design effects
[SVY] svy bootstrap Bootstrap for survey data
[SVY] bootstrap_options More options for bootstrap variance estimation
[SVY] svy brr Balanced repeated replication for survey data
[SVY] brr_options More options for BRR variance estimation
[SVY] svy jackknife Jackknife estimation for survey data
[SVY] jackknife_options More options for jackknife variance estimation
[SVY] svy sdr Successive difference replication for survey data
[SVY] sdr_options More options for SDR variance estimation

Survey data concepts

[SVY] Variance estimation Variance estimation for survey data
[SVY] Subpopulation estimation Subpopulation estimation for survey data
[SVY] Calibration Calibration for survey data
[SVY] Direct standardization Direct standardization of means, proportions, and ratios
[SVY] Poststratification Poststratification for survey data

Tools for programmers of new survey commands

[SVY] ml for svy Maximum pseudolikelihood estimation for survey data
[SVY] svymarkout Mark observations for exclusion on the basis of survey characteristics
Remarks and examples

Remarks are presented under the following headings:

- Introduction
- Survey design tools
- Survey data analysis tools
- Survey data concepts
- Tools for programmers of new survey commands
- Video examples

Introduction

Stata’s facilities for survey data analysis are centered around the *svy* prefix command. After you identify the survey design characteristics with the *svyset* command, prefix the estimation commands in your data analysis with “*svy:*”. For example, where you would normally use the *regress* command to fit a linear regression model for nonsurvey data, use *svy: regress* to fit a linear regression model for your survey data.

Why should you use the *svy* prefix command when you have survey data? To answer this question, we need to discuss some of the characteristics of survey design and survey data collection because these characteristics affect how we must perform our analysis if we want to get it right.

Survey data are characterized by the following:

- Sampling weights, also called probability weights—*pweights* in Stata’s terminology
- Cluster sampling
- Stratification

These features arise from the design and details of the data collection procedure. Here’s a brief description of how these design features affect the analysis of the data:

- *Sampling weights*. In sample surveys, observations are selected through a random process, but different observations may have different probabilities of selection. Weights are equal to (or proportional to) the inverse of the probability of being sampled. Various postsampling adjustments to the weights are sometimes made, as well. A weight of $w_j$ for the $j$th observation means, roughly speaking, that the $j$th observation represents $w_j$ elements in the population from which the sample was drawn.

Omitting weights from the analysis results in estimates that may be biased, sometimes seriously so. Sampling weights also play a role in estimating standard errors.

- *Clustering*. Individuals are not sampled independently in most survey designs. Collections of individuals (for example, counties, city blocks, or households) are typically sampled as a group, known as a *cluster*.

There may also be further subsampling within the clusters. For example, counties may be sampled, then city blocks within counties, then households within city blocks, and then finally persons within households. The clusters at the first level of sampling are called *primary sampling units* (PSUs)—in this example, counties are the PSUs. In the absence of clustering, the PSUs are defined to be the individuals, or, equivalently, clusters, each of size one.

Cluster sampling typically results in larger sample-to-sample variability than sampling individuals directly. This increased variability must be accounted for in standard error estimates, hypothesis testing, and other forms of inference.
• Stratification. In surveys, different groups of clusters are often sampled separately. These groups are called strata. For example, the 254 counties of a state might be divided into two strata, say, urban counties and rural counties. Then 10 counties might be sampled from the urban stratum, and 15 from the rural stratum.

Sampling is done independently across strata; the stratum divisions are fixed in advance. Thus strata are statistically independent and can be analyzed as such. When the individual strata are more homogeneous than the population as a whole, the homogeneity can be exploited to produce smaller (and honestly so) estimates of standard errors.

To put it succinctly: using sampling weights is important to get the point estimates right. We must consider the weighting, clustering, and stratification of the survey design to get the standard errors right. If our analysis ignores the clustering in our design, we would probably produce standard errors that are smaller than they should be. Stratification can be used to get smaller standard errors for a given overall sample size.

For more detailed introductions to complex survey data analysis, see Cochran (1977); Heeringa, West, and Berglund (2017); Kish (1965); Levy and Lemeshow (2008); Scheaffer et al.; (2012); Skinner, Holt, and Smith (1989); Stuart (1984); Thompson (2012); and Williams (1978).

Survey design tools

Before using svy, first take a quick look at [SVY] svyset. Use the svyset command to specify the variables that identify the survey design characteristics and default method for estimating standard errors. Once set, svy will automatically use these design specifications until they are cleared or changed or a new dataset is loaded into memory.

As the following two examples illustrate, svyset allows you to identify a wide range of complex sampling designs. First, we show a simple single-stage design and then a complex multistage design.

Example 1: Survey data from a one-stage design

A commonly used single-stage survey design uses clustered sampling across several strata, where the clusters are sampled without replacement. In a Stata dataset composed of survey data from this design, the survey design variables identify information about the strata, PSUs (clusters), sampling weights, and finite population correction. Here we use svyset to specify these variables, respectively named strata, su1, pw, and fpc1.

```
. use https://www.stata-press.com/data/r18/stage5a
. svyset su1 [pweight=pw], strata(strata) fpc(fpc1)
```

Sampling weights: pw
VCE: linearized
Single unit: missing
Strata 1: strata
Sampling unit 1: su1
FPC 1: fpc1

In addition to the variables we specified, svyset reports that the default method for estimating standard errors is Taylor linearization and that svy will report missing values for the standard errors when it encounters a stratum with one sampling unit (also called singleton strata).
Example 2: Multistage survey data

We have (fictional) data on American high school seniors (12th graders), and the data were collected according to the following multistage design. In the first stage, counties were independently selected within each state. In the second stage, schools were selected within each chosen county. Within each chosen school, a questionnaire was filled out by every attending high school senior. We have entered all the information into a Stata dataset called `multistage.dta`.

The survey design variables are as follows:

- `state` contains the stratum identifiers.
- `county` contains the first-stage sampling units.
- `ncounties` contains the total number of counties within each state.
- `school` contains the second-stage sampling units.
- `nschools` contains the total number of schools within each county.
- `sampwgt` contains the sampling weight for each sampled individual.

Here we load the dataset into memory and use `svyset` with the above variables to declare that these data are survey data.

```
. use https://www.stata-press.com/data/r18/multistage
. svyset county [pw=sampwgt], strata(state) fpc(ncounties) || school, fpc(nschools)
```

Sampling weights: sampwgt
VCE: linearized
Single unit: missing
Strata 1: state
Sampling unit 1: county
FPC 1: ncounties
Strata 2: <one>
Sampling unit 2: school
FPC 2: nschools

```
. save highschool
```

We saved the `svyset` dataset to `highschool.dta`. We can now use this new dataset without having to worry about respecifying the design characteristics.

```
. clear
. describe
Contains data
   Observations:         0
   Variables:            0
Sorted by:
. use highschool
. svyset
```

Sampling weights: sampwgt
VCE: linearized
Single unit: missing
Strata 1: state
Sampling unit 1: county
FPC 1: ncounties
Strata 2: <one>
Sampling unit 2: school
FPC 2: nschools
After the design characteristics have been `svyset`, you should also look at `svy:svydescribe`. Use `svydescribe` to browse each stage of your survey data; `svy:svydescribe` reports useful information on sampling unit counts, missing data, and singleton strata.

Example 3: Survey describe

Here we use `svy:svydescribe` to describe the first stage of our survey dataset of sampled high school seniors. We specified the `weight` variable to get `svy:svydescribe` to report on where it contains missing values and how this affects the estimation sample.

```
. svy:svydescribe weight
Survey: Describing stage 1 sampling units
Sampling weights: sampwgt
    VCE: linearized
    Single unit: missing
    Strata 1: state
    Sampling unit 1: county
      FPC 1: ncounties
    Strata 2: <one>
    Sampling unit 2: school
      FPC 2: nschools

<table>
<thead>
<tr>
<th>Stratum</th>
<th>Number of units included</th>
<th>Number of units omitted</th>
<th>Number of obs with complete data</th>
<th>Number of obs with missing data</th>
<th># obs per included unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>2</td>
<td>0</td>
<td>92</td>
<td>0</td>
<td>34 46.0</td>
</tr>
<tr>
<td>2</td>
<td>2</td>
<td>0</td>
<td>112</td>
<td>0</td>
<td>51 56.0</td>
</tr>
<tr>
<td>3</td>
<td>2</td>
<td>0</td>
<td>43</td>
<td>0</td>
<td>18 21.5</td>
</tr>
<tr>
<td>4</td>
<td>2</td>
<td>0</td>
<td>37</td>
<td>0</td>
<td>14 18.5</td>
</tr>
<tr>
<td>5</td>
<td>2</td>
<td>0</td>
<td>96</td>
<td>0</td>
<td>38 48.0</td>
</tr>
<tr>
<td>(output omitted)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>46</td>
<td>2</td>
<td>0</td>
<td>115</td>
<td>0</td>
<td>56 57.5</td>
</tr>
<tr>
<td>47</td>
<td>2</td>
<td>0</td>
<td>67</td>
<td>0</td>
<td>28 33.5</td>
</tr>
<tr>
<td>48</td>
<td>2</td>
<td>0</td>
<td>56</td>
<td>0</td>
<td>23 28.0</td>
</tr>
<tr>
<td>49</td>
<td>2</td>
<td>0</td>
<td>78</td>
<td>0</td>
<td>39 39.0</td>
</tr>
<tr>
<td>50</td>
<td>2</td>
<td>0</td>
<td>64</td>
<td>0</td>
<td>31 32.0</td>
</tr>
<tr>
<td></td>
<td>100</td>
<td>0</td>
<td>4,071</td>
<td>0</td>
<td>14 40.7</td>
</tr>
</tbody>
</table>

```

From the output, we gather that there are 50 strata, each stratum contains two PSUs, the PSUs vary in size, and the total sample size is 4,071 students. We can also see that there are no missing data in the `weight` variable.

Survey data analysis tools

Stata’s suite of survey data commands is governed by the `svy` prefix command; see `svy` and `svy:svy estimation`. `svy` runs the supplied estimation command while accounting for the survey design characteristics in the point estimates and variance estimation method. The available variance estimation methods are balanced repeated replication (BRR), the bootstrap, the jackknife, successive difference replication, and first-order Taylor linearization. By default, `svy` computes standard errors by using the linearized variance estimator—so called because it is based on a first-order Taylor series linear approximation (Wolter 2007). In the nonsurvey context, we refer to this variance estimator as the `robust` variance estimator, otherwise known in Stata as the Huber/White/sandwich estimator; see `robust`.
Example 4: Estimating a population mean

Here we use the `svy` prefix with the `mean` command to estimate the average weight of high school seniors in our population.

```
  . svy: mean weight
  (running mean on estimation sample)

  Survey: Mean estimation
  Number of strata = 50        Number of obs = 4,071
  Number of PSUs   = 100       Population size = 8,000,000
  Design df        = 50

  Linearized
  Mean    std. err.  [95% conf. interval]
  weight  160.2863    .7412512   158.7974   161.7751
```

In its header, `svy` reports the number of strata and PSUs from the first stage, the sample size, an estimate of population size, and the design degrees of freedom. Just like the standard output from the `mean` command, the table of estimation results contains the estimated mean and its standard error as well as a confidence interval.

Example 5: Survey regression

Here we use the `svy` prefix with the `regress` command to model the association between `weight` and `height` in our population of high school seniors.

```
  . svy: regress weight height
  (running regress on estimation sample)

  Survey: Linear regression
  Number of strata = 50        Number of obs = 4,071
  Number of PSUs   = 100       Population size = 8,000,000
  Design df        = 50
  F(1, 50)     = 593.99
  Prob > F       = 0.0000
  R-squared      = 0.2787

  Linearized
  Coefficient  std. err.  t    P>|t|   [95% conf. interval]
  weight      .7163115    .0293908 24.37  0.000   .6572784   .7753447
  _cons     -149.6183    12.57265 -11.90  0.000  -174.8712  -124.3654
```

In addition to the header elements we saw in the previous example using `svy: mean`, the command `svy: regress` also reports a model $F$ test and estimated $R^2$. Although many of Stata’s model-fitting commands report $Z$ statistics for testing coefficients against zero, `svy` always reports $t$ statistics and uses the design degrees of freedom to compute $p$-values.

The `svy` prefix can be used with many estimation commands in Stata; see [SVY] `svy estimation` for a list of estimation commands that support the `svy` prefix.
Example 6: Cox’s proportional hazards model

Suppose that we want to model the incidence of lung cancer by using three risk factors: smoking status, sex, and place of residence. Our dataset comes from a longitudinal health survey: the First National Health and Nutrition Examination Survey (NHANES I) (Miller 1973; Engel et al. 1978) and its 1992 Epidemiologic Follow-up Study (NHEFS) (Cox et al. 1997); see the National Center for Health Statistics website at https://www.cdc.gov/nchs/. We will be using data from the samples identified by NHANES I examination locations 1–65 and 66–100; thus we will svyset the revised pseudo-PSU and strata variables associated with these locations. Similarly, our pweight variable was generated using the sampling weights for the nutrition and detailed samples for locations 1–65 and the weights for the detailed sample for locations 66–100.

. use https://www.stata-press.com/data/r18/nhefs
. svyset psu2 [pw=swgt2], strata(strata2)
Sampling weights: swgt2
  VCE: linearized
  Single unit: missing
  Strata 1: strata2
  Sampling unit 1: psu2
  FPC 1: <zero>

The lung cancer information was taken from the 1992 NHEFS interview data. We use the participants’ ages for the time scale. Participants who never had lung cancer and were alive for the 1992 interview were considered censored. Participants who never had lung cancer and died before the 1992 interview were also considered censored at their age of death.

. stset age_lung_cancer [pw=swgt2], fail(lung_cancer)
Survival-time data settings
  Failure event: lung_cancer!=0 & lung_cancer<.
  Observed time interval: (0, age_lung_cancer]
  Exit on or before: failure
  Weight: [pweight=swgt2]

14,407  total observations
  5,126  event time missing (age_lung_cancer>=.)  PROBABLE ERROR
9,281  observations remaining, representing
     83  failures in single-record/single-failure data
599,691  total analysis time at risk and under observation
  At risk from t =     0
     Earliest observed entry t =     0
     Last observed exit t =     97

Although stset warns us that it is a “probable error” to have 5,126 observations with missing event times, we can verify from the 1992 NHEFS documentation that there were indeed 9,281 participants with complete information.

For our proportional hazards model, we pulled the risk factor information from the NHANES I and 1992 NHEFS datasets. Smoking status was taken from the 1992 NHEFS interview data, but we filled in all but 132 missing values by using the general medical history supplement data in NHANES I. Smoking status is represented by separate indicator variables for former smokers and current smokers; the base comparison group is nonsmokers. Sex was determined using the 1992 NHEFS vitality data and is represented by an indicator variable for males. Place-of-residence information was taken from the medical history questionnaire in NHANES I and is represented by separate indicator variables for rural and heavily populated (more than 1 million people) urban residences; the base comparison group is urban residences with populations of fewer than 1 million people.
. svy: stcox former_smoker smoker male urban1 rural
(running stcox on estimation sample)

Survey: Cox regression

<table>
<thead>
<tr>
<th></th>
<th>Number of strata = 35</th>
<th>Number of obs = 9,149</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Number of PSUs = 105</td>
<td>Population size = 151,327,827</td>
</tr>
<tr>
<td></td>
<td>Design df = 70</td>
<td>F(5, 66) = 14.07</td>
</tr>
<tr>
<td></td>
<td>Prob &gt; F = 0.0000</td>
<td></td>
</tr>
</tbody>
</table>

|            | Haz. ratio | std. err. | t  | P>|t| | [95% conf. interval] |
|------------|------------|-----------|----|-----|----------------------|
| former_smoker | 2.788113   | .6205102 | 4.61 | .000 | 1.788705 4.345923 |
| smoker      | 7.849483   | 2.593249 | 6.24 | .000 | 4.061457 15.17051 |
| male        | 1.187611   | .3445315 | 0.59 | .555 | .6658757 2.118142 |
| urban1      | .8035074   | .3285144 | -0.54 | .594 | .3555123 1.816039 |
| rural       | 1.581674   | .5281859 | 1.37 | .174 | .8125799 3.078702 |

From the above results, we can see that both former and current smokers have a significantly higher risk for developing lung cancer than do nonsmokers.

svy: tabulate can be used to produce one-way and two-way tables with survey data and can produce survey-adjusted tests of independence for two-way contingency tables; see [SVY] svy: tabulate oneway and [SVY] svy: tabulate twoway.

Example 7: Two-way tables for survey data

With data from the Second National Health and Nutrition Examination Survey (NHANES II) (McDowell et al. 1981), we use svy: tabulate to produce a two-way table of cell proportions along with their standard errors and confidence intervals (the survey design characteristics have already been svyset). We also use the format() option to get svy: tabulate to report the cell values and marginals to four decimal places.
use https://www.stata-press.com/data/r18/nhanes2b
.svy: tabulate race diabetes, row se ci format(%7.4f)
(running tabulate on estimation sample)

Number of strata = 31  Number of obs = 10,349
Number of PSUs = 62  Population size = 117,131,111
Design df = 31

Diabetes status  
Race  Not diab  Diabetic  Total
White  0.9680  0.0320  1.0000
   (0.0020) (0.0020)
   [0.9638,0.9718] [0.0282,0.0362]
Black  0.9410  0.0590  1.0000
   (0.0061) (0.0061)
   [0.9271,0.9523] [0.0477,0.0729]
Other  0.9797  0.0203  1.0000
   (0.0076) (0.0076)
   [0.9566,0.9906] [0.0094,0.0434]
Total  0.9658  0.0342  1.0000
   (0.0018) (0.0018)
   [0.9619,0.9693] [0.0307,0.0381]

Key: Row proportion
(Linearized standard error of row proportion)
[95% confidence interval for row proportion]

Pearson:
Uncorrected  chi2(2) = 21.3483
Design-based  F(1.52, 47.26) =  15.0056  P = 0.0000

.svy: tabulate has many options, such as the format() option, for controlling how the table looks. See [SVY] svy: tabulate twoway for a discussion of the different design-based and unadjusted tests of association.

Example 8: Comparing means

Going back to our high school survey data in example 2, we estimate the mean of weight (in pounds) for each subpopulation identified by the categories of the sex variable (male and female).
. use https://www.stata-press.com/data/r18/highschool
. svy: mean weight, over(sex)
(running mean on estimation sample)
Survey: Mean estimation
Number of strata = 50             Number of obs = 4,071
Number of PSUs = 100            Population size = 8,000,000
Design df = 50

Survey: Mean estimation

<table>
<thead>
<tr>
<th></th>
<th>Linearized</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>std. err.</td>
<td>[95% conf. interval]</td>
</tr>
<tr>
<td>c.weight@sex</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Male</td>
<td>175.4809</td>
<td>1.116802</td>
<td>173.2377 177.7241</td>
</tr>
<tr>
<td>Female</td>
<td>146.2040</td>
<td>.9004157</td>
<td>144.3955 148.0125</td>
</tr>
</tbody>
</table>

Here we use the test command to test the hypothesis that the average male is 30 pounds heavier than the average female; from the results, we cannot reject this hypothesis at the 5% level.

. test weight#1.sex - weight#2.sex = 30

Adjusted Wald test
( 1) c.weight@1bn.sex - c.weight@2.sex = 30
F( 1, 50) = 0.23
Prob > F = 0.6353

estat has specific subroutines for use after svy; see [SVY] estat.

• estat svyset reports the survey design settings used to produce the current estimation results.
• estat effects and estat 1ceffects report a table of design and misspecification effects for point estimates and linear combinations of point estimates, respectively.
• estat size reports a table of sample and subpopulation sizes after svy: mean, svy: proportion, svy: ratio, and svy: total.
• estat sd reports subpopulation standard deviations on the basis of the estimation results from mean and svy: mean.
• estat strata reports the number of singleton and certainty strata within each sampling stage.
• estat cv reports the coefficient of variation for each coefficient in the current estimation results.
• estat gof reports a goodness-of-fit test for binary response models using survey data.
Example 9: Design effects

Here we use `estat effects` to report the design effects DEFF and DEFT for the mean estimates from the previous example.

```
. estat effects
```

<table>
<thead>
<tr>
<th>Over</th>
<th>Linearized</th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Mean</td>
<td>std. err.</td>
<td>DEFF</td>
<td>DEFT</td>
</tr>
<tr>
<td>c.weight@sex</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Male</td>
<td>175.4809</td>
<td>1.116802</td>
<td>2.61016</td>
<td>1.61519</td>
<td></td>
</tr>
<tr>
<td>Female</td>
<td>146.204</td>
<td>.9004157</td>
<td>1.7328</td>
<td>1.31603</td>
<td></td>
</tr>
</tbody>
</table>

Note: Weights must represent population totals for DEFF to be correct when using an FPC; however, DEFT is invariant to the scale of weights.

Now we use `estat lceffects` to report the design effects DEFF and DEFT for the difference of the mean estimates from the previous example.

```
. estat lceffects weight#1.sex - weight#2.sex
```

```
( 1) c.weight@1bn.sex - c.weight@2.sex = 0
```

<table>
<thead>
<tr>
<th>Mean</th>
<th>Coefficient</th>
<th>Std. err.</th>
<th>DEFF</th>
<th>DEFT</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1)</td>
<td>29.27691</td>
<td>1.515201</td>
<td>2.42759</td>
<td>1.55768</td>
</tr>
</tbody>
</table>

Note: Weights must represent population totals for DEFF to be correct when using an FPC; however, DEFT is invariant to the scale of weights.

The `svy brr` prefix command produces point and variance estimates by using the BRR method; see [SVY] `svy brr`. BRR was first introduced by McCarthy (1966, 1969a, and 1969b) as a method of variance estimation for designs with two PSUs in every stratum. The BRR variance estimator tends to give more reasonable variance estimates for this design than the linearized variance estimator, which can result in large values and undesirably wide confidence intervals.

The `svy jackknife` prefix command produces point and variance estimates by using the jackknife replication method; see [SVY] `svy jackknife`. The jackknife is a data-driven variance estimation method that can be used with model-fitting procedures for which the linearized variance estimator is not implemented, even though a linearized variance estimator is theoretically possible to derive (Shao and Tu 1995).

To protect the privacy of survey participants, public survey datasets may contain replicate-weight variables instead of variables that identify the PSUs and strata. These replicate-weight variables can be used with the appropriate replication method for variance estimation instead of the linearized variance estimator; see [SVY] `svyset`.

The `svy brr` and `svy jackknife` prefix commands can be used with those commands that may not be fully supported by `svy` but are compatible with the BRR and the jackknife replication methods. They can also be used to produce point estimates for expressions of estimation results from a prefixed command.

The `svy bootstrap` and `svy sdr` prefix commands work only with replicate weights. Both assume that you have obtained these weight variables externally.
The `svy bootstrap` prefix command produces variance estimates that have been adjusted for bootstrap sampling. Bootstrap sampling of complex survey has become more popular in recent years and is the variance-estimation method used in the National Population Health Survey conducted by Statistics Canada; see [SVY] `svy bootstrap` and [SVY] `Variance estimation` for more details.

The `svy sdr` prefix command produces variance estimates that implement successive difference replication (SDR), first introduced by Fay and Train (1995) as a method for annual demographic supplements to the Current Population Survey. This method is typically applied to systematic samples where the observed sampling units follow a natural order; see [SVY] `svy sdr` and [SVY] `Variance estimation` for more details.

Example 10: BRR and replicate-weight variables

The survey design for the NHANES II data (McDowell et al. 1981) is specifically suited to BRR: there are two PSUs in every stratum.

```
. use https://www.stata-press.com/data/r18/nhanes2
. svydescribe
Survey: Describing stage 1 sampling units
Sampling weights: finalwgt
VCE: linearized
Single unit: missing
Strata 1: strata
Sampling unit 1: psu
FPC 1: <zero>

<table>
<thead>
<tr>
<th>Stratum</th>
<th># units</th>
<th># obs</th>
<th>Number of obs per unit</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>Min</td>
</tr>
<tr>
<td>1</td>
<td>2</td>
<td>380</td>
<td>165</td>
</tr>
<tr>
<td>2</td>
<td>2</td>
<td>185</td>
<td>67</td>
</tr>
<tr>
<td>3</td>
<td>2</td>
<td>348</td>
<td>149</td>
</tr>
<tr>
<td>4</td>
<td>2</td>
<td>460</td>
<td>229</td>
</tr>
<tr>
<td>5</td>
<td>2</td>
<td>252</td>
<td>105</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>29</td>
<td>2</td>
<td>503</td>
<td>215</td>
</tr>
<tr>
<td>30</td>
<td>2</td>
<td>365</td>
<td>166</td>
</tr>
<tr>
<td>31</td>
<td>2</td>
<td>308</td>
<td>143</td>
</tr>
<tr>
<td>32</td>
<td>2</td>
<td>450</td>
<td>211</td>
</tr>
<tr>
<td>31</td>
<td>62</td>
<td>10,351</td>
<td>67</td>
</tr>
</tbody>
</table>
```

Here is a privacy-conscious dataset equivalent to the one above; all the variables and values remain, except that `strata` and `psu` are replaced with BRR replicate-weight variables. The BRR replicate-weight variables are already `svyset`, and the default method for variance estimation is `vce(brr)`.
Survey — Introduction to survey commands

Suppose that we were interested in the population ratio of weight to height. Here we use total to estimate the population totals of weight and height and the svy brr prefix to estimate their ratio and variance; we use total instead of ratio (which is otherwise preferable here) to show how to specify an expression when using svy: brr.

```
. svy brr WtoH = (_b[weight]/_b[height]): total weight height
```

BRR results

```
BRR replications (32): ........10.........20.........30.. done
BRR results
Command: total weight height
WtoH: _b[weight]/_b[height]
```

<table>
<thead>
<tr>
<th></th>
<th>BRR</th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coefficient</td>
<td>std. err.</td>
<td>t</td>
<td>P&gt;</td>
<td>t</td>
</tr>
<tr>
<td>-------</td>
<td>-----------------</td>
<td>-----------</td>
<td>-------</td>
<td>-------</td>
<td>----------------------</td>
</tr>
<tr>
<td>WtoH</td>
<td>.4268116</td>
<td>.0008904</td>
<td>479.36</td>
<td>0.000</td>
<td>.4249957</td>
</tr>
</tbody>
</table>

Survey data concepts

The variance estimation methods that Stata uses are discussed in [SVY] Variance estimation.

Subpopulation estimation involves computing point and variance estimates for part of the population. This method is not the same as restricting the estimation sample to the collection of observations within the subpopulation because variance estimation for survey data measures sample-to-sample variability, assuming that the same survey design is used to collect the data. Use the subpop() option of the svy prefix to perform subpopulation estimation, and use if and in only when you need to make restrictions on the estimation sample; see [SVY] Subpopulation estimation.

Example 11: Subpopulation estimation

Here we will use our svyset high school data to model the association between weight and height in the subpopulation of male high school seniors. First, we describe the sex variable to determine how to identify the males in the dataset. We then use label list to verify that the variable label agrees with the value labels.
. use https://www.stata-press.com/data/r18/highschool
. describe sex

<table>
<thead>
<tr>
<th>Variable name</th>
<th>Storage type</th>
<th>Display format</th>
<th>Value label</th>
<th>Variable label</th>
</tr>
</thead>
<tbody>
<tr>
<td>sex</td>
<td>byte</td>
<td>%9.0g</td>
<td>sex</td>
<td>Sex</td>
</tr>
</tbody>
</table>

. label list sex

sex:
   1 Male
   2 Female

Here we generate a variable named `male` so that we can easily identify the male high school seniors. We specified `if !missing(sex)`: doing so will cause the generated `male` variable to contain a missing value at each observation where the `sex` variable does. This is done on purpose (although it is not necessary if `sex` is free of missing values) because missing values should not be misinterpreted to imply female.

. generate male = sex == 1 if !missing(sex)

Now we specify `subpop(male)` as an option to the `svy` prefix in our model fit.

. svy, subpop(male): regress weight height
   (running `regress` on estimation sample)

Survey: Linear regression

<table>
<thead>
<tr>
<th>Number of strata</th>
<th>Number of obs</th>
<th>Population size</th>
<th>Subpop. no. obs</th>
<th>Subpop. size</th>
<th>Design df</th>
<th>F(1, 50)</th>
<th>Prob &gt; F</th>
<th>R-squared</th>
</tr>
</thead>
<tbody>
<tr>
<td>50</td>
<td>4,071</td>
<td>8,000,000</td>
<td>1,938</td>
<td>3,848,021</td>
<td>50</td>
<td>225.38</td>
<td>0.000</td>
<td>0.2347</td>
</tr>
</tbody>
</table>

| Weight | Coefficient | std. err. | t      | P>|t| | [95% conf. interval] |
|--------|-------------|-----------|--------|------|----------------------|
| height | .7632911    | .0508432  | 15.01  | 0.000 | .6611696 - .8654127 |
| _cons  | -168.6532   | 22.5708   | -7.47  | 0.000 | -213.988 -123.3184  |

Although the table of estimation results contains the same columns as earlier, `svy` reports some extra subpopulation information in the header. Here the extra header information tells us that 1,938 of the 4,071 sampled high school seniors are male, and the estimated number of male high school seniors in the population is 3,848,021.

Direct standardization is an estimation method that allows comparing rates that come from different frequency distributions; see [SVY] Direct standardization. In direct standardization, estimated rates (means, proportions, and ratios) are adjusted according to the frequency distribution of a standard population. The standard population is partitioned into categories, called standard strata. The stratum frequencies for the standard population are called standard weights. In the standardizing frequency distribution, the standard strata are most commonly identified by demographic information such as age, sex, and ethnicity. The standardized rate estimate is the weighted sum of unadjusted rates, where the weights are the relative frequencies taken from the standardizing frequency distribution. Direct standardization is available with `svy: mean`, `svy: proportion`, and `svy: ratio`. 
Example 12: Standardized rates

Table 3.12-6 of Korn and Graubard (1999, 156) contains enumerated data for two districts of London for the years 1840–1841. The age variable identifies the age groups in 5-year increments, bgliving contains the number of people living in the Bethnal Green district at the beginning of 1840, bgdeaths contains the number of people who died in Bethnal Green that year, hsliving contains the number of people living in St. George’s Hanover Square at the beginning of 1840, and hsdeaths contains the number of people who died in Hanover Square that year.

```
use https://www.stata-press.com/data/r18/stdize, clear
list, noobs sep(0) sum
```

<table>
<thead>
<tr>
<th>age</th>
<th>bgliving</th>
<th>bgdeaths</th>
<th>hsliving</th>
<th>hsdeaths</th>
</tr>
</thead>
<tbody>
<tr>
<td>0-5</td>
<td>10739</td>
<td>850</td>
<td>5738</td>
<td>463</td>
</tr>
<tr>
<td>5-10</td>
<td>9180</td>
<td>76</td>
<td>4591</td>
<td>55</td>
</tr>
<tr>
<td>10-15</td>
<td>8006</td>
<td>38</td>
<td>4148</td>
<td>28</td>
</tr>
<tr>
<td>15-20</td>
<td>7096</td>
<td>37</td>
<td>6168</td>
<td>36</td>
</tr>
<tr>
<td>20-25</td>
<td>6579</td>
<td>38</td>
<td>9440</td>
<td>68</td>
</tr>
<tr>
<td>25-30</td>
<td>5829</td>
<td>51</td>
<td>8675</td>
<td>78</td>
</tr>
<tr>
<td>30-35</td>
<td>5749</td>
<td>51</td>
<td>7513</td>
<td>64</td>
</tr>
<tr>
<td>35-40</td>
<td>4490</td>
<td>56</td>
<td>5091</td>
<td>78</td>
</tr>
<tr>
<td>40-45</td>
<td>4385</td>
<td>47</td>
<td>4930</td>
<td>85</td>
</tr>
<tr>
<td>45-50</td>
<td>2955</td>
<td>66</td>
<td>2883</td>
<td>66</td>
</tr>
<tr>
<td>50-55</td>
<td>2995</td>
<td>74</td>
<td>2711</td>
<td>77</td>
</tr>
<tr>
<td>55-60</td>
<td>1644</td>
<td>67</td>
<td>1275</td>
<td>55</td>
</tr>
<tr>
<td>60-65</td>
<td>1835</td>
<td>64</td>
<td>1469</td>
<td>61</td>
</tr>
<tr>
<td>65-70</td>
<td>1042</td>
<td>64</td>
<td>649</td>
<td>55</td>
</tr>
<tr>
<td>70-75</td>
<td>879</td>
<td>68</td>
<td>619</td>
<td>58</td>
</tr>
<tr>
<td>75-80</td>
<td>366</td>
<td>47</td>
<td>233</td>
<td>51</td>
</tr>
<tr>
<td>80-85</td>
<td>173</td>
<td>39</td>
<td>136</td>
<td>20</td>
</tr>
<tr>
<td>85-90</td>
<td>71</td>
<td>22</td>
<td>48</td>
<td>15</td>
</tr>
<tr>
<td>90-95</td>
<td>21</td>
<td>6</td>
<td>10</td>
<td>4</td>
</tr>
<tr>
<td>95-100</td>
<td>4</td>
<td>2</td>
<td>2</td>
<td>1</td>
</tr>
<tr>
<td>unknown</td>
<td>50</td>
<td>1</td>
<td>124</td>
<td>0</td>
</tr>
</tbody>
</table>

Sum 74088 1764 66453 1418

We can use `svy: ratio` to compute the deathrates for each district in 1840. Because this dataset is identified as census data, we will create an FPC variable that will contain a sampling rate of 100%. This method will result in zero standard errors, which are interpreted to mean no variability—appropriate because our point estimates came from the entire population.
. generate fpc = 1
. svyset, fpc(fpc)

Sampling weights: <none>
VCE: linearized
Single unit: missing
Strata 1: <one>
Sampling unit 1: <observations>
FPC 1: fpc

. svy: ratio (Bethnal: bgdeaths/bgliving) (Hanover: hsdeaths/hsliving)
(running ratio on estimation sample)

Survey: Ratio estimation
Number of strata = 1 Number of obs = 21
Number of PSUs = 21 Population size = 21
Design df = 20

Bethnal: bgdeaths/bgliving
Hanover: hsdeaths/hsliving

<table>
<thead>
<tr>
<th></th>
<th>Linearized</th>
<th>[95% conf. interval]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bethnal</td>
<td>.0238095</td>
<td>0</td>
</tr>
<tr>
<td>Hanover</td>
<td>.0213384</td>
<td>0</td>
</tr>
</tbody>
</table>

Note: Zero standard errors because of 100% sampling rate detected for FPC in the first stage.

The deathrates are 2.38% for Bethnal Green and 2.13% for St. George’s Hanover Square. These observed deathrates are not really comparable because they come from two different age distributions. We can standardize based on the age distribution from Bethnal Green. Here age identifies our standard strata and bgliving contains the associated population sizes.

. svy: ratio (Bethnal: bgdeaths/bgliving) (Hanover: hsdeaths/hsliving),
> stdize(age) stdweight(bgliving)
(running ratio on estimation sample)

Survey: Ratio estimation
Number of strata = 1 Number of obs = 21
Number of PSUs = 21 Population size = 21
N. of std strata = 21 Design df = 20

Bethnal: bgdeaths/bgliving
Hanover: hsdeaths/hsliving

<table>
<thead>
<tr>
<th></th>
<th>Linearized</th>
<th>[95% conf. interval]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bethnal</td>
<td>.0238095</td>
<td>0</td>
</tr>
<tr>
<td>Hanover</td>
<td>.0266409</td>
<td>0</td>
</tr>
</tbody>
</table>

Note: Zero standard errors because of 100% sampling rate detected for FPC in the first stage.

The standardized deathrate for St. George’s Hanover Square, 2.66%, is larger than the deathrate for Bethnal Green.

Calibration and poststratification are methods for adjusting the sampling weights, usually to account for underrepresented groups in the population; see [SVY] Calibration and [SVY] Poststratification. These methods usually result in decreasing bias that is due to nonresponse and underrepresented
groups in the population. They also tend to result in smaller variance estimates. Calibration and poststratification are available for all survey estimation commands and are specified using `svyset`; see `SVY svyset`.

#### Example 13: Poststratified mean

Levy and Lemeshow (2008, sec. 6.6) give an example of poststratification by using simple survey data from a veterinarian’s client list. The data in `poststrata.dta` were collected using simple random sampling (SRS) without replacement. The `totexp` variable contains the total expenses to the client, `type` identifies the cats and dogs, `postwgt` contains the poststratum sizes (450 for cats and 850 for dogs), and `fpc` contains the total number of clients (850 + 450 = 1300).

```
. use https://www.stata-press.com/data/r18/poststrata, clear
. svyset, poststrata(type) postweight(postwgt) fpc(fpc)
Sampling weights: <none>
   VCE: linearized
Poststrata: type
Post. pop. sizes: postwgt
   Single unit: missing
   Strata 1: <one>
   Sampling unit 1: <observations>
   FPC 1: fpc
. svy: mean totexp
(running mean on estimation sample)
Survey: Mean estimation
Number of strata = 1       Number of obs   =    50
Number of PSUs  =    50     Population size = 1,300
N. of poststrata = 2       Design df   =     49

                   Linearized
         Mean   std. err.    [95% conf. interval]
totexp      40.11513  1.163498      37.77699    42.45327
```

The mean total expenses is $40.12 with a standard error of $1.16. In the following, we omit the poststratification information from `svyset`, resulting in mean total expenses of $39.73 with standard error $2.22. The difference between the mean estimates is explained by the facts that expenses tend to be larger for dogs than for cats and that the dogs were slightly underrepresented in the sample (850/1,300 ≈ 0.65 for the population; 32/50 = 0.64 for the sample). This reasoning also explains why the variance estimate from the poststratified mean is smaller than the one that was not poststratified.
Tools for programmers of new survey commands

The `ml` command can be used to fit a model by the method of maximum likelihood. When the `svy` option is specified, `ml` performs maximum pseudolikelihood, applying sampling weights and design-based linearization automatically; see [R] `ml` and Gould, Pitblado, and Poi (2010).

Example 14

The `ml` command requires a program that computes likelihood values to perform maximum likelihood. Here is a likelihood evaluator used in Gould, Pitblado, and Poi (2010) to fit linear regression models using the likelihood from the normal distribution.

```
program mynormal_lf
    version 18.0
    args lnf mu lnsigma
    quietly replace `lnf' = ln(normalden($ML_y1,`mu',exp(`lnsigma')))
end
```

Back in example 5, we fit a linear regression model using the high school survey data. Here we use `ml` and `mynormal_lf` to fit the same survey regression model.
svymarkout is a programmer’s command that resets the values in a variable that identifies the estimation sample, dropping observations for which any of the survey characteristic variables contain missing values. This tool is most helpful for developing estimation commands that use ml to fit models using maximum pseudolikelihood directly, instead of relying on the svy prefix.

**Video examples**

Basic introduction to the analysis of complex survey data in Stata
How to download, import, and merge multiple datasets from the NHANES website
How to download, import, and prepare data from the NHANES website

**Acknowledgments**

Many of the svy commands were developed in collaboration with John L. Eltinge of the U.S. Census Bureau. We thank him for his invaluable assistance.

We thank Wayne Johnson of the National Center for Health Statistics for providing the NHANES II dataset.

We thank Nicholas Winter of the Politics Department at the University of Virginia for his diligent efforts to keep Stata up to date with mainstream variance estimation methods for survey data, as well as for providing versions of svy brr and svy jackknife.
William Gemmell Cochran (1909–1980) was born in Rutherglen, Scotland, and educated at the Universities of Glasgow and Cambridge. He accepted a post at Rothamsted before finishing his doctorate. Cochran emigrated to the United States in 1939 and worked at Iowa State, North Carolina State, Johns Hopkins, and Harvard. He made many major contributions across several fields of statistics, including experimental design, the analysis of counted data, sample surveys, and observational studies, and was author or coauthor (with Gertrude M. Cox and George W. Snedecor) of various widely used texts.

Leslie Kish (1910–2000) was born in Poprad, Hungary, and entered the United States with his family in 1926. He worked as a lab assistant at the Rockefeller Institute for Medical Research and studied at the College of the City of New York, fighting in the Spanish Civil War before receiving his first degree in mathematics. Kish worked for the Bureau of the Census, the Department of Agriculture, the Army Air Corps, and the University of Michigan. He carried out pioneering work in the theory and practice of survey sampling, including design effects, BRR, response errors, rolling samples and censuses, controlled selection, multipurpose designs, and small-area estimation.

References


Also see

[SVY] **svy** — The survey prefix command

[SVY] **svy estimation** — Estimation commands for survey data

[SVY] **svyset** — Declare survey design for dataset

[P] **_robust** — Robust variance estimates