

survey — Introduction to survey commands

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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] [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] [svyremarkout](#) Mark observations for exclusion on the basis of survey characteristics

Remarks and examples

Remarks are presented under the following headings:

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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 \(2010\)](#); [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 http://www.stata-press.com/data/r13/stage5a
. svyset su1 [pweight=pw], strata(strata) fpc(fpc1)
      pweight: pw
      VCE: linearized
Single unit: missing
Strata 1: strata
  SU 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 http://www.stata-press.com/data/r13/multistage
. svyset county [pw=sampwgt], strata(state) fpc(ncounties) || school, fpc(nschools)
      pweight: sampwgt
      VCE: linearized
Single unit: missing
Strata 1: state
      SU 1: county
      FPC 1: ncounties
Strata 2: <one>
      SU 2: school
      FPC 2: nschools
. save highschool
file highschool.dta saved
```

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
  obs:          0
  vars:          0
  size:          0
Sorted by:
. use highschool
. svyset
      pweight: sampwgt
      VCE: linearized
Single unit: missing
Strata 1: state
      SU 1: county
      FPC 1: ncounties
Strata 2: <one>
      SU 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; `svydescribe` reports useful information on sampling unit counts, missing data, and singleton strata.

▷ Example 3: Survey describe

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

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

Stratum	#Units included	#Units omitted	#Obs with complete data	#Obs with missing data	#Obs per included Unit		
					min	mean	max
1	2	0	92	0	34	46.0	58
2	2	0	112	0	51	56.0	61
3	2	0	43	0	18	21.5	25
4	2	0	37	0	14	18.5	23
5	2	0	96	0	38	48.0	58
<i>(output omitted)</i>							
46	2	0	115	0	56	57.5	59
47	2	0	67	0	28	33.5	39
48	2	0	56	0	23	28.0	33
49	2	0	78	0	39	39.0	39
50	2	0	64	0	31	32.0	33
50	100	0	4071	0	14	40.7	81
			4071				

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.

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Survey data analysis tools

Stata's suite of survey data commands is governed by the `svy` prefix command; see [\[SVY\] 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 [\[P\] _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   =      4071
Number of PSUs   =     100      Population size = 8000000
                                   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.

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▷ 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   =      4071
Number of PSUs   =     100      Population size = 8000000
                                   Design df        =         50
                                   F( 1, 50)         =      593.99
                                   Prob > F          =      0.0000
                                   R-squared         =      0.2787
```

weight	Linearized				
	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
height	.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.

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The `svy` prefix can be used with many estimation commands in Stata. Here is the list of estimation commands that support the `svy` prefix.

Descriptive statistics

<code>mean</code>	[R] mean — Estimate means
<code>proportion</code>	[R] proportion — Estimate proportions
<code>ratio</code>	[R] ratio — Estimate ratios
<code>total</code>	[R] total — Estimate totals

Linear regression models

<code>cnsreg</code>	[R] cnsreg — Constrained linear regression
<code>etregress</code>	[TE] etregress — Linear regression with endogenous treatment effects
<code>glm</code>	[R] glm — Generalized linear models
<code>intreg</code>	[R] intreg — Interval regression
<code>nl</code>	[R] nl — Nonlinear least-squares estimation
<code>regress</code>	[R] regress — Linear regression
<code>tobit</code>	[R] tobit — Tobit regression
<code>truncreg</code>	[R] truncreg — Truncated regression

Structural equation models

<code>sem</code>	[SEM] sem — Structural equation model estimation command
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Survival-data regression models

<code>stcox</code>	[ST] stcox — Cox proportional hazards model
<code>streg</code>	[ST] streg — Parametric survival models

Binary-response regression models

<code>biprobit</code>	[R] biprobit — Bivariate probit regression
<code>cloglog</code>	[R] cloglog — Complementary log-log regression
<code>hetprobit</code>	[R] hetprobit — Heteroskedastic probit model
<code>logistic</code>	[R] logistic — Logistic regression, reporting odds ratios
<code>logit</code>	[R] logit — Logistic regression, reporting coefficients
<code>probit</code>	[R] probit — Probit regression
<code>scobit</code>	[R] scobit — Skewed logistic regression

Discrete-response regression models

<code>clogit</code>	[R] clogit — Conditional (fixed-effects) logistic regression
<code>mlogit</code>	[R] mlogit — Multinomial (polytomous) logistic regression
<code>mprobit</code>	[R] mprobit — Multinomial probit regression
<code>ologit</code>	[R] ologit — Ordered logistic regression
<code>oprobit</code>	[R] oprobit — Ordered probit regression
<code>slogit</code>	[R] slogit — Stereotype logistic regression

Poisson regression models

<code>gnbreg</code>	Generalized negative binomial regression in [R] nbreg
<code>nbreg</code>	[R] nbreg — Negative binomial regression
<code>poisson</code>	[R] poisson — Poisson regression
<code>tnbreg</code>	[R] tnbreg — Truncated negative binomial regression
<code>tpoisson</code>	[R] tpoisson — Truncated Poisson regression
<code>zinb</code>	[R] zinb — Zero-inflated negative binomial regression
<code>zip</code>	[R] zip — Zero-inflated Poisson regression

Instrumental-variables regression models

<code>ivprobit</code>	[R] ivprobit — Probit model with continuous endogenous regressors
<code>ivregress</code>	[R] ivregress — Single-equation instrumental-variables regression
<code>ivtobit</code>	[R] ivtobit — Tobit model with continuous endogenous regressors

Regression models with selection

<code>heckman</code>	[R] heckman — Heckman selection model
<code>heckoprobit</code>	[R] heckoprobit — Ordered probit model with sample selection
<code>heckprobit</code>	[R] heckprobit — Probit model with sample selection

▷ **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 <http://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 http://www.stata-press.com/data/r13/nhefs
. svyset psu2 [pw=swgt2], strata(strata2)
      pweight: swgt2
      VCE: linearized
Single unit: missing
Strata 1: strata2
SU 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)
      failure event: lung_cancer != 0 & lung_cancer < .
obs. time interval: (0, age_lung_cancer]
      exit on or before: failure
                weight: [pweight=swgt2]
```

```
14407 total observations
 5126 event time missing (age_lung_cancer>=.)          PROBABLE ERROR
```

```
 9281 observations remaining, representing
    83 failures in single-record/single-failure data
599691 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

```
Number of strata =      35          Number of obs   =      9149
Number of PSUs   =     105          Population size = 151327827
                                     Design df       =        70
                                     F( 5, 66)         =      14.07
                                     Prob > F         =      0.0000
```

_t	Linearized		t	P> t	[95% Conf. Interval]	
	Haz. Ratio	Std. Err.				
former_smoker	2.788113	.6205102	4.61	0.000	1.788705	4.345923
smoker	7.849483	2.593249	6.24	0.000	4.061457	15.17051
male	1.187611	.3445315	0.59	0.555	.6658757	2.118142
urban1	.8035074	.3285144	-0.54	0.594	.3555123	1.816039
rural	1.581674	.5281859	1.37	0.174	.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 http://www.stata-press.com/data/r13/nhanes2b
. svy: tabulate race diabetes, row se ci format(%7.4f)
(running tabulate on estimation sample)
Number of strata   =          31          Number of obs       =       10349
Number of PSUs    =          62          Population size     =    117131111
                                   Design df           =           31
```

1=white, 2=black, 3=other	diabetes, 1=yes, 0=no		Total
	0	1	
White	0.9680 (0.0020) [0.9638,0.9718]	0.0320 (0.0020) [0.0282,0.0362]	1.0000
Black	0.9410 (0.0061) [0.9271,0.9523]	0.0590 (0.0061) [0.0477,0.0729]	1.0000
Other	0.9797 (0.0076) [0.9566,0.9906]	0.0203 (0.0076) [0.0094,0.0434]	1.0000
Total	0.9658 (0.0018) [0.9619,0.9693]	0.0342 (0.0018) [0.0307,0.0381]	1.0000

Key: row proportions
(linearized standard errors of row proportions)
[95% confidence intervals for row proportions]

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.

All the standard postestimation commands (for example, `estimates`, `lincom`, `margins`, `nlcom`, `test`, `testnl`) are also available after `svy`.

▷ 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 http://www.stata-press.com/data/r13/highschool
. svy: mean weight, over(sex)
(running mean on estimation sample)

Survey: Mean estimation
Number of strata =      50      Number of obs   =    4071
Number of PSUs   =     100      Population size = 8000000
                                   Design df       =      50

      male: sex = male
      female: sex = female
```

Over	Linearized		
	Mean	Std. Err.	[95% Conf. Interval]
<code>weight</code>			
male	175.4809	1.116802	173.2377 177.7241
female	146.204	.9004157	144.3955 148.0125

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]male - [weight]female = 30
Adjusted Wald test
( 1) [weight]male - [weight]female = 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 lceffects` 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
      male: sex = male
      female: sex = female
```

Over	Linearized		DEFF	DEFT
	Mean	Std. Err.		
weight				
male	175.4809	1.116802	2.61016	1.61519
female	146.204	.9004157	1.7328	1.31603

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]male - [weight]female
(1) [weight]male - [weight]female = 0
```

Mean	Coef.	Std. Err.	DEFF	DEFT
(1)	29.27691	1.515201	2.42759	1.55768

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

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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 http://www.stata-press.com/data/r13/nhanes2
. svydescribe
```

```
Survey: Describing stage 1 sampling units
```

```
  pweight: finalwgt
          VCE: linearized
Single unit: missing
Strata 1: strata
  SU 1: psu
  FPC 1: <zero>
```

Stratum	#Units	#Obs	#Obs per Unit		
			min	mean	max
1	2	380	165	190.0	215
2	2	185	67	92.5	118
3	2	348	149	174.0	199
4	2	460	229	230.0	231
5	2	252	105	126.0	147
<i>(output omitted)</i>					
29	2	503	215	251.5	288
30	2	365	166	182.5	199
31	2	308	143	154.0	165
32	2	450	211	225.0	239
31	62	10351	67	167.0	288

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)`.

```

. use http://www.stata-press.com/data/r13/nhanes2brr
. svyset
      pweight: finalwgt
      VCE: brr
      MSE: off
      brrweight: brr_1 brr_2 brr_3 brr_4 brr_5 brr_6 brr_7 brr_8 brr_9 brr_10
                brr_11 brr_12 brr_13 brr_14 brr_15 brr_16 brr_17 brr_18 brr_19
                brr_20 brr_21 brr_22 brr_23 brr_24 brr_25 brr_26 brr_27 brr_28
                brr_29 brr_30 brr_31 brr_32
      Single unit: missing
      Strata 1: <one>
      SU 1: <observations>
      FPC 1: <zero>

```

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
(running total on estimation sample)
BRR replications (32)
-----|-----|-----|-----|-----|-----|
.....|.....|.....|.....|.....|.....|
BRR results
Number of obs      =      10351
Population size    =    117157513
Replications       =         32
Design df         =         31

command: total weight height
WtoH:    _b[weight]/_b[height]

```

	BRR				
	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
WtoH	.4268116	.0008904	479.36	0.000	.4249957 .4286276

◀

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 http://www.stata-press.com/data/r13/highschool
. describe sex

```

variable name	storage type	display format	value label	variable label
sex	byte	%9.0g	sex	1=male, 2=female

```

. 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

```

Number of strata	=	50	Number of obs	=	4071
Number of PSUs	=	100	Population size	=	8000000
			Subpop. no. of obs	=	1938
			Subpop. size	=	3848021.4
			Design df	=	50
			F(1, 50)	=	225.38
			Prob > F	=	0.0000
			R-squared	=	0.2347

weight	Linearized		t	P> t	[95% Conf. Interval]	
	Coef.	Std. Err.				
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 (rounded down).

◀

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 http://www.stata-press.com/data/r13/stdize, clear
. list, noobs sep(0) sum
```

	age	bgliving	bgdeaths	hsliving	hsdeaths
	0-5	10739	850	5738	463
	5-10	9180	76	4591	55
	10-15	8006	38	4148	28
	15-20	7096	37	6168	36
	20-25	6579	38	9440	68
	25-30	5829	51	8675	78
	30-35	5749	51	7513	64
	35-40	4490	56	5091	78
	40-45	4385	47	4930	85
	45-50	2955	66	2883	66
	50-55	2995	74	2711	77
	55-60	1644	67	1275	55
	60-65	1835	64	1469	61
	65-70	1042	64	649	55
	70-75	879	68	619	58
	75-80	366	47	233	51
	80-85	173	39	136	20
	85-90	71	22	48	15
	90-95	21	6	10	4
	95-100	4	2	2	1
	unknown	50	1	124	0
Sum		74088	1764	66453	1418

We can use `svy: ratio` to compute the death rates 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.


```

. gen fpc = 1
. svyset, fpc(fpc)
    pweight: <none>
      VCE: linearized
Single unit: missing
Strata 1: <one>
  SU 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

```

	Linearized		
	Ratio	Std. Err.	[95% Conf. Interval]
Bethnal	.0238095	0	. .
Hanover	.0213384	0	. .

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

The death rates are 2.38% for Bethnal Green and 2.13% for St. George's Hanover Square. These observed death rates 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

```

	Linearized		
	Ratio	Std. Err.	[95% Conf. Interval]
Bethnal	.0238095	0	. .
Hanover	.0266409	0	. .

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

The standardized death rate for St. George's Hanover Square, 2.66%, is larger than the death rate for Bethnal Green.

◀

Poststratification is a method for adjusting the sampling weights, usually to account for under-represented groups in the population; see [SVY] [poststratification](#). This method usually results in decreasing bias because of nonresponse and underrepresented groups in the population. It also tends to

result in smaller variance estimates. Poststratification is available for all survey estimation commands and is 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 http://www.stata-press.com/data/r13/poststrata, clear
. svyset, poststrata(type) postweight(postwgt) fpc(fpc)
      pweight: <none>
      VCE: linearized
      Poststrata: type
      Postweight: postwgt
      Single unit: missing
      Strata 1: <one>
      SU 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 =    1300
N. of poststrata =      2      Design df     =      49
```

	Linearized			
	Mean	Std. Err.	[95% Conf. Interval]	
<code>totexp</code>	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 ($850/1,300 \approx 0.65$ 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.

```

. svyset, fpc(fpc)
    pweight: <none>
      VCE: linearized
Single unit: missing
Strata 1: <one>
  SU 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 =     50
                                   Design df      =     49

```

	Linearized		
	Mean	Std. Err.	[95% Conf. Interval]
totexp	39.7254	2.221747	35.26063 44.19017

◀

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 13
    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.

```

. use http://www.stata-press.com/data/r13/highschool
. ml model lf mynormal_lf (mu: weight = height) /lnsigma, svy
. ml max

initial:      log pseudolikelihood =      -<inf>   (could not be evaluated)
feasible:     log pseudolikelihood = -7.301e+08
rescale eq:  log pseudolikelihood = -51944380
Iteration 0:  log pseudolikelihood = -47565331
Iteration 1:  log pseudolikelihood = -41221759 (not concave)
Iteration 2:  log pseudolikelihood = -41218957 (not concave)
Iteration 3:  log pseudolikelihood = -41170544 (not concave)
Iteration 4:  log pseudolikelihood = -41145411 (not concave)
Iteration 5:  log pseudolikelihood = -41123161 (not concave)
Iteration 6:  log pseudolikelihood = -41103001 (not concave)
Iteration 7:  log pseudolikelihood = -41083551
Iteration 8:  log pseudolikelihood = -38467683 (backed up)
Iteration 9:  log pseudolikelihood = -38329015
Iteration 10: log pseudolikelihood = -38328739
Iteration 11: log pseudolikelihood = -38328739

Number of strata   =      50                Number of obs     =      4071
Number of PSUs    =     100                Population size   =     8000000
                                                Design df        =         50
                                                F( 1, 50)        =     593.99
                                                Prob > F         =         0.0000

```

weight	Linearized		t	P> t	[95% Conf. Interval]	
	Coef.	Std. Err.				
mu						
height	.7163115	.0293908	24.37	0.000	.6572784	.7753447
_cons	-149.6183	12.57265	-11.90	0.000	-174.8712	-124.3654
lnsigma						
_cons	3.372154	.0180777	186.54	0.000	3.335844	3.408464

◀

`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 example

[Basic introduction to the analysis of complex survey data in Stata](#)

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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.

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Also see

- [SVY] **svyset** — Declare survey design for dataset
- [SVY] **svy** — The survey prefix command
- [SVY] **svy estimation** — Estimation commands for survey data
- [P] **_robust** — Robust variance estimates