Title

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svy estimation — Estimation commands for survey data

Description Menu Remarks and examples References Also see

Description

Survey data analysis in Stata is essentially the same as standard data analysis. The standard syntax applies; you just need to also remember the following:

- Use `svyset` to identify the survey design characteristics.
- Prefix the estimation commands with `svy:`.

For example,

```
. use http://www.stata-press.com/data/r15/nhanes2f
. svyset psuid [pweight=finalwgt], strata(stratid)
. svy: regress zinc age c.age#c.age weight female black orace rural
```

See [SVY] **svyset** and [SVY] **svy**.

The following estimation commands support the `svy` prefix:

Descriptive statistics

`mean`	[R] **mean** — Estimate means
`proportion`	[R] **proportion** — Estimate proportions
`ratio`	[R] **ratio** — Estimate ratios
`total`	[R] **total** — Estimate totals

Linear regression models

`churdle`	[R] **churdle** — Cragg hurdle regression
`cnsreg`	[R] **cnsreg** — Constrained linear regression
`eintreg`	[ERM] **eintreg** — Extended interval regression
`eregress`	[ERM] **eregress** — Extended linear regression
`etregress`	[TE] **etregress** — Linear regression with endogenous treatment effects
`glm`	[R] **glm** — Generalized linear models
`hetregress`	[R] **hetregress** — Heteroskedastic linear regression
`intreg`	[R] **intreg** — Interval regression
`nl`	[R] **nl** — Nonlinear least-squares estimation
`regress`	[R] **regress** — Linear regression
`tobit`	[R] **tobit** — Tobit regression
`truncreg`	[R] **truncreg** — Truncated regression

Structural equation models

`sem`	[SEM] **sem** — Structural equation model estimation command
`gsem`	[SEM] **gsem** — Generalized structural equation model estimation command

Survival-data regression models

stcox	[ST] **stcox** — Cox proportional hazards model
stintreg	[ST] **stintreg** — Parametric models for interval-censored survival-time data
streg	[ST] **streg** — Parametric survival models

Binary-response regression models

biprobit	[R] **biprobit** — Bivariate probit regression
cloglog	[R] **cloglog** — Complementary log-log regression
eprobit	[ERM] **eprobit** — Extended probit regression
hetprobit	[R] **hetprobit** — Heteroskedastic probit model
logistic	[R] **logistic** — Logistic regression, reporting odds ratios
logit	[R] **logit** — Logistic regression, reporting coefficients
probit	[R] **probit** — Probit regression
scobit	[R] **scobit** — Skewed logistic regression

Discrete-response regression models

asmixlogit	[R] **asmixlogit** — Alternative-specific mixed logit regression
clogit	[R] **clogit** — Conditional (fixed-effects) logistic regression
eoprobit	[ERM] **eoprobit** — Extended ordered probit regression
mlogit	[R] **mlogit** — Multinomial (polytomous) logistic regression
mprobit	[R] **mprobit** — Multinomial probit regression
ologit	[R] **ologit** — Ordered logistic regression
oprobit	[R] **oprobit** — Ordered probit regression
slogit	[R] **slogit** — Stereotype logistic regression
zioprobit	[R] **zioprobit** — Zero-inflated ordered probit regression

Fractional-response regression models

betareg	[R] **betareg** — Beta regression
fracreg	[R] **fracreg** — Fractional response regression

Poisson regression models

cpoisson	[R] **cpoisson** — Censored Poisson regression
etpoisson	[TE] **etpoisson** — Poisson regression with endogenous treatment effects
gnbreg	Generalized negative binomial regression in [R] **nbreg**
nbreg	[R] **nbreg** — Negative binomial regression
poisson	[R] **poisson** — Poisson regression
tnbreg	[R] **tnbreg** — Truncated negative binomial regression
tpoisson	[R] **tpoisson** — Truncated Poisson regression
zinb	[R] **zinb** — Zero-inflated negative binomial regression
zip	[R] **zip** — Zero-inflated Poisson regression

Instrumental-variables regression models

ivprobit	[R] **ivprobit** — Probit model with continuous endogenous covariates
ivregress	[R] **ivregress** — Single-equation instrumental-variables regression
ivtobit	[R] **ivtobit** — Tobit model with continuous endogenous covariates

Regression models with selection

heckman	[R] **heckman** — Heckman selection model
heckoprobit	[R] **heckoprobit** — Ordered probit model with sample selection
heckpoisson	[R] **heckpoisson** — Poisson regression with sample selection
heckprobit	[R] **heckprobit** — Probit model with sample selection

Multilevel mixed-effects models

mecloglog	[ME] **mecloglog** — Multilevel mixed-effects complementary log-log regression
meglm	[ME] **meglm** — Multilevel mixed-effects generalized linear model
meintreg	[ME] **meintreg** — Multilevel mixed-effects interval regression
melogit	[ME] **melogit** — Multilevel mixed-effects logistic regression
menbreg	[ME] **menbreg** — Multilevel mixed-effects negative binomial regression
meologit	[ME] **meologit** — Multilevel mixed-effects ordered logistic regression
meoprobit	[ME] **meoprobit** — Multilevel mixed-effects ordered probit regression
mepoisson	[ME] **mepoisson** — Multilevel mixed-effects Poisson regression
meprobit	[ME] **meprobit** — Multilevel mixed-effects probit regression
mestreg	[ME] **mestreg** — Multilevel mixed-effects parametric survival models
metobit	[ME] **metobit** — Multilevel mixed-effects tobit regression

Finite mixture models

fmm: betareg	[FMM] **fmm: betareg** — Finite mixtures of beta regression models
fmm: cloglog	[FMM] **fmm: cloglog** — Finite mixtures of complementary log-log regression models
fmm: glm	[FMM] **fmm: glm** — Finite mixtures of generalized linear regression models
fmm: intreg	[FMM] **fmm: intreg** — Finite mixtures of interval regression models
fmm: ivregress	[FMM] **fmm: ivregress** — Finite mixtures of linear regression models with endogenous covariates
fmm: logit	[FMM] **fmm: logit** — Finite mixtures of logistic regression models
fmm: mlogit	[FMM] **fmm: mlogit** — Finite mixtures of multinomial (polytomous) logistic regression models
fmm: nbreg	[FMM] **fmm: nbreg** — Finite mixtures of negative binomial regression models
fmm: ologit	[FMM] **fmm: ologit** — Finite mixtures of ordered logistic regression models
fmm: oprobit	[FMM] **fmm: oprobit** — Finite mixtures of ordered probit regression models
fmm: pointmass	[FMM] **fmm: pointmass** — Finite mixtures models with a density mass at a single point
fmm: poisson	[FMM] **fmm: poisson** — Finite mixtures of Poisson regression models
fmm: probit	[FMM] **fmm: probit** — Finite mixtures of probit regression models
fmm: regress	[FMM] **fmm: regress** — Finite mixtures of linear regression models
fmm: streg	[FMM] **fmm: streg** — Finite mixtures of parametric survival models
fmm: tobit	[FMM] **fmm: tobit** — Finite mixtures of tobit regression models
fmm: tpoisson	[FMM] **fmm: tpoisson** — Finite mixtures of truncated Poisson regression models
fmm: truncreg	[FMM] **fmm: truncreg** — Finite mixtures of truncated linear regression models

Item response theory

irt 1pl	[IRT] **irt 1pl** — One-parameter logistic model
irt 2pl	[IRT] **irt 2pl** — Two-parameter logistic model

`irt 3pl`	[IRT] **irt 3pl** — Three-parameter logistic model
`irt grm`	[IRT] **irt grm** — Graded response model
`irt nrm`	[IRT] **irt nrm** — Nominal response model
`irt pcm`	[IRT] **irt pcm** — Partial credit model
`irt rsm`	[IRT] **irt rsm** — Rating scale model
`irt hybrid`	[IRT] **irt hybrid** — Hybrid IRT models

Menu

Statistics > Survey data analysis > ...

Dialog boxes for all statistical estimators that support `svy` can be found on the above menu path. In addition, you can access survey data estimation from standard dialog boxes on the **SE/Robust** or **SE/Cluster** tab.

Remarks and examples

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Remarks are presented under the following headings:

Overview of survey analysis in Stata

Many Stata commands estimate the parameters of a process or population by using sample data. For example, `mean` estimates means, `ratio` estimates ratios, `regress` fits linear regression models, `poisson` fits Poisson regression models, and `logistic` fits logistic regression models. Some of these *estimation commands* support the `svy` prefix, that is, they may be prefixed by `svy:` to produce results appropriate for complex survey data. Whereas `poisson` is used with standard, nonsurvey data, `svy: poisson` is used with survey data. In what follows, we refer to any estimation command not prefixed by `svy:` as the standard command. A standard command prefixed by `svy:` is referred to as a `svy` command.

Most standard commands (and all standard commands supported by `svy`) allow `pweights` and the `vce(cluster` *clustvar*`)` option, where *clustvar* corresponds to the PSU variable that you `svyset`. If your survey data exhibit only sampling weights or first-stage clusters (or both), you can get by with using the standard command with `pweights`, `vce(cluster` *clustvar*`)`, or both. Your parameter estimates will always be identical to those you would have obtained from the `svy` command, and the standard command uses the same robust (linearization) variance estimator as the `svy` command with a similarly `svyset` design.

Most standard commands are also fit using maximum likelihood. When used with independently distributed, nonweighted data, the likelihood to be maximized reflects the joint probability distribution of the data given the chosen model. With complex survey data, however, this interpretation of the likelihood is no longer valid, because survey data are weighted, not independently distributed, or both. Yet for survey data, (valid) parameter estimates for a given model can be obtained using the associated likelihood function with appropriate weighting. Because the probabilistic interpretation no longer holds, the likelihood here is instead called a *pseudolikelihood*, but likelihood-ratio tests are no longer valid. See Skinner (1989, sec. 3.4.4) for a discussion of maximum pseudolikelihood estimators.

Here we highlight the other features of svy commands:

- svy commands handle stratified sampling, but none of the standard commands do. Because stratification usually makes standard errors smaller, ignoring stratification is usually conservative. So not using svy with stratified sample data is not a terrible thing to do. However, to get the smallest possible "honest" standard-error estimates for stratified sampling, use svy.

- svy commands use t statistics with $n - L$ degrees of freedom to test the significance of coefficients, where n is the total number of sampled PSUs (clusters) and L is the number of strata in the first stage. Some of the standard commands use t statistics, but most use z statistics. If the standard command uses z statistics for its standard variance estimator, then it also uses z statistics with the robust (linearization) variance estimator. Strictly speaking, t statistics are appropriate with the robust (linearization) variance estimator; see [P] **_robust** for the theoretical rationale. But, using z rather than t statistics yields a nontrivial difference only when there is a small number of clusters (< 50). If a regression model command uses t statistics and the vce(cluster *clustvar*) option is specified, then the degrees of freedom used is the same as that of the svy command (in the absence of stratification).

- svy commands produce an adjusted Wald test for the model test, and test can be used to produce adjusted Wald tests for other hypotheses after svy commands. Only unadjusted Wald tests are available if the svy prefix is not used. The adjustment can be important when the degrees of freedom, $n - L$, is small relative to the dimension of the test. (If the dimension is one, then the adjusted and unadjusted Wald tests are identical.) This fact along with the point made in the second bullet make using the svy command important if the number of sampled PSUs (clusters) is small (< 50).

- svy: regress differs slightly from regress and svy: ivregress differs slightly from ivregress in that they use different multipliers for the variance estimator. regress and ivregress (when the small option is specified) use a multiplier of $\{(N-1)/(N-k)\}\{n/(n-1)\}$, where N is the number of observations, n is the number of clusters (PSUs), and k is the number of regressors including the constant. svy: regress and svy: ivregress use $n/(n-1)$ instead. Thus they produce slightly different standard errors. The $(N-1)/(N-k)$ is ad hoc and has no rigorous theoretical justification; hence, the purist svy commands do not use it. The svy commands tacitly assume that $N \gg k$. If $(N-1)/(N-k)$ is not close to 1, you may be well advised to use regress or ivregress so that some punishment is inflicted on your variance estimates. Maximum likelihood estimators in Stata (for example, logit) do no such adjustment but rely on the sensibilities of the analyst to ensure that N is reasonably larger than k. Thus the maximum pseudolikelihood estimators (for example, svy: logit) produce the same standard errors as the corresponding maximum likelihood commands (for example, logit), but p-values are slightly different because of the point made in the second bullet.

- svy commands can produce proper estimates for subpopulations by using the subpop() option. Using an if restriction with svy or standard commands can yield incorrect standard-error estimates for subpopulations. Often an if restriction will yield the same standard error as subpop(); most other times, the two standard errors will be slightly different; but sometimes—usually for thinly sampled subpopulations—the standard errors can be appreciably different. Hence, the svy command with the subpop() option should be used to obtain estimates for thinly sampled subpopulations. See [SVY] **subpopulation estimation** for more information.

- svy commands handle zero sampling weights properly. Standard commands ignore any observation with a weight of zero. Usually, this will yield the same standard errors, but sometimes they will differ. Sampling weights of zero can arise from various postsampling adjustment procedures. If the sum of weights for one or more PSUs is zero, svy and standard commands will produce different standard errors, but usually this difference is very small.

- You can `svyset iweights` and let these weights be negative. Negative sampling weights can arise from various postsampling adjustment procedures. If you want to use negative sampling weights, then you must `svyset iweights` instead of `pweights`; no standard command will allow negative sampling weights.
- The `svy` commands compute finite population corrections (FPCs).
- After a `svy` command, `estat effects` will compute the design effects DEFF and DEFT and the misspecification effects MEFF and MEFT.
- `svy` commands can perform variance estimation that accounts for multiple stages of clustered sampling.
- `svy` commands can perform variance estimation that accounts for poststratification adjustments to the sampling weights.
- Some standard options are not allowed with the `svy` prefix. For example, `vce()` and weights cannot be specified when using the `svy` prefix because `svy` is already using the variance estimation and sampling weights identified by `svyset`. Some options are not allowed with survey data because they would be statistically invalid, such as `noskip` for producing optional likelihood-ratio tests. Other options are not allowed because they change how estimation results are reported (for example, `nodisplay`, `first`, `plus`) or are not compatible with `svy`'s variance estimation methods (for example, `irls`, `mse1`, `hc2`, `hc3`).
- Estimation results are presented in the standard way, except that `svy` has its own table header: In addition to the sample size, model test, and R^2 (if present in the output from the standard command), `svy` will also report the following information in the header:
    a. number of strata and PSUs
    b. number of poststrata, if specified to `svyset`
    c. population size estimate
    d. subpopulation sizes, if the `subpop()` option was specified
    e. design degrees of freedom

Descriptive statistics

Use `svy: mean`, `svy: ratio`, `svy: proportion`, and `svy: total` to estimate finite population and subpopulation means, ratios, proportions, and totals, respectively. You can also estimate standardized means, ratios, and proportions for survey data; see [SVY] **direct standardization**. Estimates for multiple subpopulations can be obtained using the `over()` option; see [SVY] **subpopulation estimation**.

▷ Example 1

Suppose that we need to estimate the average birthweight for the population represented by the National Maternal and Infant Health Survey (NMIHS) (Gonzalez, Krauss, and Scott 1992).

First, we gather the survey design information.

- Primary sampling units are mothers; that is, PSUs are individual observations—there is no separate PSU variable.
- The `finalwgt` variable contains the sampling weights.
- The `stratan` variable identifies strata.
- There is no variable for the finite population correction.

Then we use `svyset` to identify the variables for sampling weights and stratification.

```
. use http://www.stata-press.com/data/r15/nmihs
. svyset [pweight=finwgt], strata(stratan)
      pweight: finwgt
          VCE: linearized
  Single unit: missing
     Strata 1: stratan
         SU 1: <observations>
        FPC 1: <zero>
```

Now we can use `svy: mean` to estimate the average birthweight for our population.

```
. svy: mean birthwgt
(running mean on estimation sample)
Survey: Mean estimation
Number of strata =       6        Number of obs    =      9,946
Number of PSUs   =   9,946        Population size =  3,895,562
                                  Design df        =      9,940
```

	Mean	Linearized Std. Err.	[95% Conf.	Interval]
birthwgt	3355.452	6.402741	3342.902	3368.003

From these results, we are 95% confident that the mean birthweight for our population is between 3,343 and 3,368 grams.

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Regression models

As exhibited in the table at the beginning of this manual entry, many of Stata's regression model commands support the `svy` prefix. If you know how to use one of these commands with standard data, then you can also use the corresponding `svy` command with your survey data.

▷ Example 2

Let's model the incidence of high blood pressure with a dataset from the Second National Health and Nutrition Examination Survey (NHANES II) (McDowell et al. 1981). The survey design characteristics are already `svyset`, so we will just replay them.

```
. use http://www.stata-press.com/data/r15/nhanes2d
. svyset
      pweight: finalwgt
          VCE: linearized
  Single unit: missing
     Strata 1: strata
         SU 1: psu
        FPC 1: <zero>
```

Now we can use `svy: logistic` to model the incidence of high blood pressure as a function of height, weight, age, and sex (using the `female` indicator variable).

```
. svy: logistic highbp height weight age female
(running logistic on estimation sample)

Survey: Logistic regression

Number of strata   =        31                Number of obs     =       10,351
Number of PSUs     =        62                Population size   =  117,157,513
                                              Design df         =           31
                                              F(   4,     28)   =       368.33
                                              Prob > F          =       0.0000

------------------------------------------------------------------------------
             |             Linearized
      highbp | Odds Ratio   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      height |   .9657022   .0051511    -6.54   0.000     .9552534    .9762654
      weight |   1.053023   .0026902    20.22   0.000     1.047551    1.058524
         age |   1.050059   .0019761    25.96   0.000     1.046037    1.054097
      female |   .6272129   .0368195    -7.95   0.000     .5564402     .706987
       _cons |    .716868   .6106878    -0.39   0.699     .1261491    4.073749
------------------------------------------------------------------------------
Note: _cons estimates baseline odds.
```

The odds ratio for the `female` predictor is 0.63 (rounded to two decimal places) and is significantly less than 1. This finding implies that females have a lower incidence of high blood pressure than do males.

Here we use the `subpop()` option to model the incidence of high blood pressure in the subpopulation identified by the `female` variable.

```
. svy, subpop(female): logistic highbp height weight age
(running logistic on estimation sample)

Survey: Logistic regression

Number of strata   =        31                Number of obs     =       10,351
Number of PSUs     =        62                Population size   =  117,157,513
                                              Subpop. no. obs   =        5,436
                                              Subpop. size      =   60,998,033
                                              Design df         =           31
                                              F(   3,     29)   =       227.53
                                              Prob > F          =       0.0000

------------------------------------------------------------------------------
             |             Linearized
      highbp | Odds Ratio   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      height |   .9630557   .0074892    -4.84   0.000     .9479018    .9784518
      weight |   1.053197    .003579    15.25   0.000     1.045923    1.060522
         age |   1.066112   .0034457    19.81   0.000     1.059107    1.073163
       _cons |   .3372393   .4045108    -0.91   0.372      .029208    3.893807
------------------------------------------------------------------------------
Note: _cons estimates baseline odds.
```

Because the odds ratio for the `age` predictor is significantly greater than 1, we can conclude that older females are more likely to have high blood pressure than are younger females.

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Health surveys

There are many sources of bias when modeling the association between a disease and its risk factors (Korn, Graubard, and Midthune 1997; Korn and Graubard 1999, sec. 3.7). In cross-sectional health surveys, inference is typically restricted to the target population as it stood when the data were collected. This type of survey cannot capture the fact that participants may change their habits over time. Some health surveys collect data retrospectively, relying on the participants to recall the status of risk factors as they stood in the past. This type of survey is vulnerable to recall bias.

Longitudinal surveys collect data over time, monitoring the survey participants over several years. Although the above biases are minimized, analysts are still faced with some tough choices/situations when modeling time-to-event data. For example:

- Time scale. When studying cancer, should we measure the time scale by using the participant's age or the initial date from which data were collected?
- Time-varying covariates. Were all relevant risk factors sampled over time, or do we have only the baseline measurement?
- Competing risks. When studying mortality, do we have the data specific to cause of death?

Binder (1983) provides the foundation for fitting most of the common parametric models by using survey data. Similarly, Lin and Wei (1989) provide the foundational theory for robust inference by using the proportional hazards model. Binder (1992) describes how to estimate standard errors for the proportional hazards model from survey data, and Lin (2000) provides a rigorous justification for Binder's method. Korn and Graubard (1999) discuss many aspects of model fitting by using data from health surveys. O'Donnell et al. (2008, chap. 10) use Stata survey commands to perform multivariate analysis using health survey data.

▷ Example 3: 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/r15/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]
--------------------------------------------------------------------------
     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

Number of strata   =        35                Number of obs      =         9,149
Number of PSUs     =       105                Population size    =   151,327,827
                                              Design df          =            70
                                              F(   5,     66)    =         14.07
                                              Prob > F           =        0.0000
```

_t	Haz. Ratio	Linearized Std. Err.	t	P>|t|	[95% Conf.	Interval]
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.

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❑ Technical note

In the previous example, we specified a sampling weight variable in the calls to both `svyset` and `stset`. When the `svy` prefix is used with `stcox` and `streg`, it identifies the sampling weight variable by using the data characteristics from both `svyset` and `stset`. `svy` will report an error if the `svyset pweight` variable is different from the `stset pweight` variable. The `svy` prefix will use the specified `pweight` variable, even if it is `svyset` but not `stset`. If a `pweight` variable is `stset` but not `svyset`, `svy` will note that it will be using the `stset pweight` variable and then `svyset` it.

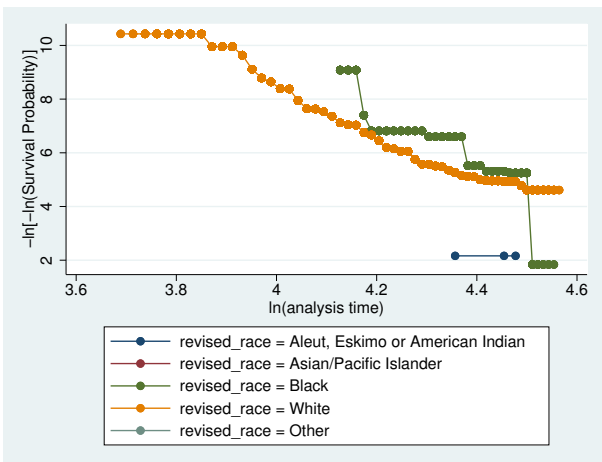
The standard st commands will not use the `svyset pweight` variable if it is not also `stset`.

❑

▷ Example 4: Multiple baseline hazards

We can assess the proportional-hazards assumption across the observed race categories for the model fit in the previous example. The race information in our 1992 NHEFS dataset is contained in the `revised_race` variable. We will use `stphplot` to produce a log-log plot for each category of `revised_race`. As described in [ST] **stcox PH-assumption tests**, if the plotted lines are reasonably parallel, the proportional-hazards assumption has not been violated. We will use the `zero` option to reset the risk factors to their base comparison group.

```
. stphplot, strata(revised_race) adjust(former_smoker smoker male urban1 rural)
> zero legend(col(1))
        failure _d:  lung_cancer
  analysis time _t:  age_lung_cancer
            weight:  [pweight=swgt2]
```



As we can see from the graph produced above, the lines for the black and white race categories intersect. This indicates a violation of the proportional-hazards assumption, so we should consider using separate baseline hazard functions for each race category in our model fit. We do this next, by specifying `strata(revised_race)` in our call to `svy: stcox`.

```
. svy: stcox former_smoker smoker male urban1 rural, strata(revised_race)
(running stcox on estimation sample)

Survey: Cox regression

Number of strata   =        35                  Number of obs      =         9,149
Number of PSUs     =       105                  Population size    =   151,327,827
                                                Design df          =            70
                                                F(   5,     66)    =         13.95
                                                Prob > F           =        0.0000
```

_t	Haz. Ratio	Linearized Std. Err.	t	P>|t|	[95% Conf.	Interval]
former_smoker	2.801797	.6280352	4.60	0.000	1.791761	4.381201
smoker	7.954921	2.640022	6.25	0.000	4.103709	15.42038
male	1.165724	.3390339	0.53	0.600	.6526527	2.082139
urban1	.784031	.3120525	-0.61	0.543	.3544764	1.73412
rural	1.490269	.5048569	1.18	0.243	.7582848	2.928851

Stratified by revised_race

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Also see

[SVY] **svy postestimation** — Postestimation tools for svy

[SVY] **estat** — Postestimation statistics for survey data

[SVY] **direct standardization** — Direct standardization of means, proportions, and ratios

[SVY] **poststratification** — Poststratification for survey data

[SVY] **subpopulation estimation** — Subpopulation estimation for survey data

[SVY] **variance estimation** — Variance estimation for survey data

[U] 20 Estimation and postestimation commands

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

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