Modelling Complex Survey Data Using R, SAS, SPSS and Stata: A Comparison Using CLSA Datasets

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Abstract The R software has become popular among researchers due to its flexibility and open-source nature. However, researchers in the fields of public health and epidemiological studies are more customary to commercial statistical softwares such as SAS, SPSS and Stata. This paper provides a comprehensive comparison on analysis of health survey data using the R survey package, SAS, SPSS and Stata. We describe detailed R codes and procedures for other software packages on commonly encountered statistical analyses, such as estimation of population means and regression analysis, using datasets from the Canadian Longitudinal Study on Aging (CLSA). It is hoped that the paper stimulates interest among health science researchers to carry data analysis using R and also serves as a cookbook for statistical analysis using different software packages.

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1. Introduction

Health-care researchers use survey data to evaluate the prevalence rates of particular diseases in a population, to establish association and causation among important health factors and measures, and to inform the creation and implementation of new health policies. For example, the goal of the Canadian Longitudinal Study of Aging (CLSA) is to facilitate vital research on healthy aging with impact, to investigate health evidence and to propose policies for aging Canadians (Raina et al. (2019)).

As recognized in the literature (Damico (2009); Lumley (2010)) and used by researchers from many scientific fields, R is an open-source and powerful statistical software with high capabilities in data manipulation and high potential for different types of presentation. In recent years, the development of RStudio, one of R’s graphic user interfaces, has facilitated use of the R program to analyze data and to visualize results. However, the R program still has not become widely adopted as the preferred statistical platform in the fields of public health and epidemiological studies. This is partly due to the lack of appropriate R codes and examples in publicly available technical documents presented in a systematic manner, and the concerns on the results as compared to those from established commercial software packages. The unawareness of similarities and differences between R and existing commercial software packages makes researchers reluctant to shift to using R as their primary statistical software.

The main objective of this paper is to describe the main steps required to model complex survey data using R, SAS, SPSS and Stata, with particular attention to dataset preparation, data importation and detailed statistical analyses using the CLSA datasets, and to produce the finite population estimates commonly reported by health researchers. The secondary objective of the paper is to provide R examples for the analyses and to promote R as a preferred platform for researchers in related fields.

This article compares estimates and standard errors from various statistical procedures implemented by selected proprietary statistical packages, namely SAS, SPSS and Stata, with those of the survey package in R, using data from the Canadian Longitudinal Study on Aging (CLSA). We compute the standard errors by the Taylor series linearization with the variance estimator of the Hansen-Hurwitz estimator (Lumley (2004)) adjusted by the finite population correction factor, which is the default option for all the survey packages we compared.

The rest of the paper is organized as follows. In Section 2, we provide the rationale for using sampling weights in the statistical analysis of survey data. In Section 3, we briefly describe the sampling framework of the CLSA. We provide codes for data import and preparation for survey analysis in Section 4. We compare the syntax, estimates and standard errors of survey summary procedures across different survey packages in Section 5. For regression analyses, we recommend to use the analytic weights, and provide the detailed descriptions in Section 6. In Section 7, we discuss subpopulation (i.e., domain) analysis in the survey context. Lastly, we provide some concluding remarks in Section 8.

2. Preliminaries of survey sampling

The purpose of statistical analyses in survey sampling is to make inferences about the target finite population from the information available in a survey sample. To obtain the sample, we select a subset of units from the population through a known sampling scheme and measure variables of interest for all selected units. The following picture illustrates the relationship between the population and the sample and the connections through sampling and inference.

![Population and Sample Diagram](image)

Most real world survey samples are selected by a without-replacement sampling method with unequal inclusion probabilities. The general estimation theory is built based on the Horvitz-Thompson estimator (Horvitz and Thompson (1952)) using the first order inclusion probabilities. Variance estimation typically requires second order inclusion probabilities, which are often unavailable in practice for a given survey dataset. Two other major features of survey designs, namely, stratification and clustering, require additional details for point and variance estimation. Variance formulas under
with-replacement sampling methods based on the Hansen-Hurwitz estimator (Hansen and Hurwitz (1943)) have much simpler forms and are easy to implement. Even if the original survey sample is selected without-replacement, it is common practice for survey data analysis to treat the sample as if the units are selected with-replacement for the purpose of variance estimation. The resulting variance estimators are valid if the sampling fractions of the original survey sample are small and the variance estimates become more conservative otherwise; see Lohr (2010) and Wu and Thompson (2020) for further details.

In what follows, we present theoretical details for stratified single-stage sampling, which is the sampling design used by CLSA (Canadian Longitudinal Study on Aging (2011); Raina et al. (2019)). Under a stratified sampling design, the population is (sometimes naturally) divided into non-overlapping subpopulations called "strata". Within each stratum, individual units are selected based on a probability sampling design. The following notations are used for stratified sampling.

| Notation | Meaning |
|----------|---------|
| $H$      | the number of strata |
| $S_h$    | the set of sampled units from stratum $h$, $h = 1, \ldots, H$ |
| $S$      | the pooled sample, $S = \bigcup_{h=1}^{H} S_h$ |
| $N_h$    | the total number of units in stratum $h$, $h = 1, \ldots, H$ |
| $N$      | the total number of units in the population, $N = \sum_{h=1}^{H} N_h$ |
| $n$      | the overall sample size, $n = \sum_{h=1}^{H} n_h$ |
| $\pi_h$  | sample inclusion probability of unit $i$ in stratum $h$ |
| $\pi_{hi}$ | joint inclusion probability of units $i$ and $i'$ in stratum $h$ |
| $w_{hi}$ | the stratum design weight, $w_{hi} = \pi_i^{-1}$ |
| $y_{hi}$ | the value of the study variable $y$ for unit $i$ in stratum $h$ |
| $E_h$    | the value of covariates $x$ for unit $i$ in stratum $h$ |

The survey dataset can be represented by \{ $(y_{hi}, x_{hi}, w_{hi}), i_h \in S_h, h = 1, \ldots, H$ \}.

**Estimation of population means**

In survey sampling, basic inferential procedures are developed for the estimation of finite population means. For the study variable $y$, the population mean under stratification is given by

$$\mu_y = \frac{1}{N} \sum_{h=1}^{H} \sum_{i=1}^{n_h} y_{hi}. \quad (1)$$

Estimation of a disease prevalence is a special case of estimating a population proportion with a binary study variable $y$. The design-unbiased Horvitz-Thompson estimator of $\mu_y$ is given by

$$\hat{\mu}_{yHT} = \frac{1}{\hat{N}} \sum_{h=1}^{H} \sum_{i \in S_h} w_{hi} y_{hi}. \quad (2)$$

The stratum design weight $w_{hi} = \pi_i^{-1}$ is often interpreted as the number of units in the population represented by the unit $i_h$ in the sample (Lohr (2010); Wu and Thompson (2020)). The Horvitz-Thompson estimator for the population total $T_y = \sum_{h=1}^{H} \sum_{i=1}^{N_h} y_{hi}$ is given by $\hat{T}_{yHT} = \sum_{h=1}^{H} \sum_{i \in S_h} w_{hi} y_{hi}$, which is also called the expansion estimator. The design weight $w_{hi}$ is also called the inflation weight. The population size $N$ is sometimes unknown to data users. An unbiased estimator of $N$ is given by $\hat{N} = \sum_{h=1}^{H} \sum_{i \in S_h} w_{hi}$. The resulting estimator of $\mu_y$ is the so-called Hájek estimator given by $\hat{\mu}_{yHT} = \frac{\hat{T}_{yHT}}{\hat{N}}$.

The theoretical design-based variance of the Horvitz-Thompson estimator given in (2) involves both the first-order and the second-order sample inclusion probabilities $\pi_i$ and $\pi_{hi}$. Under stratified sampling, the stratum samples $S_h, h = 1, \ldots, H$ are independent. The general theoretical variance
formula is given by

$$\text{Var}(\hat{\beta}_{yHT}) = N^{-2} \sum_{h=1}^{H} \text{Var} \left( \sum_{i_h \in S_h} \frac{y_{i_h}}{\pi_{i_h}} \right)$$

$$= N^{-2} \sum_{h=1}^{H} \left[ \frac{N_h}{n_h} \sum_{i_h \in S_h} \sum_{i_h' \in \delta_h} \left( \pi_{i_h'\delta_h} - \pi_{i_h}\pi_{i_h'} \right) \frac{w_{i_h} y_{i_h}}{\pi_{i_h}} \frac{w_{i_h'} y_{i_h}}{\pi_{i_h'}} \right]$$

The conventional unbiased variance estimator for the Horvitz-Thompson estimator is given by

$$\hat{\text{Var}}(\hat{\beta}_{yHT}) = N^{-2} \sum_{h=1}^{H} \left[ \frac{N_h}{n_h} \sum_{i_h \in S_h} \sum_{i_h' \in \delta_h} \left( \pi_{i_h'\delta_h} - \pi_{i_h}\pi_{i_h'} \right) \frac{w_{i_h} y_{i_h}}{\pi_{i_h}} \frac{w_{i_h'} y_{i_h}}{\pi_{i_h'}} \right]. \quad (3)$$

In practice, complex survey datasets, such as the CLSA datasets used in this paper, usually do not provide the joint inclusion probabilities \( \pi_{i_h'\delta_h} \) which are required for computing the variance estimator given in (3). Most statistical software packages for survey data analyses use approximate variance estimators to bypass this difficulty.

When sampled units are drawn with replacement, with selection probabilities \( z_{i_h}, i_h = 1, \ldots, N_h \) for each selection, the Hansen-Hurwitz estimator (Hansen and Hurwitz (1943)) of \( \mu_y \) has the same algebraic form of the Horvitz-Thompson estimator if we let \( \pi_{i_h} = n_h z_{i_h} \). The unbiased variance estimator for the Hansen-Hurwitz estimator is given by

$$\hat{\text{Var}}(\hat{\beta}_{yHT}) = N^{-2} \left[ \frac{1}{n_h(n_h-1)} \sum_{i_h \in S_h} \left( n_h w_{i_h} y_{i_h} - \sum_{i_h' \in S_h} w_{i_h'} y_{i_h} \right)^2 \right]. \quad (4)$$

The variance estimator \( \hat{\text{Var}} \) does not involve second-order inclusion probabilities and provides a good approximation to the variance estimator given in (3) if the sampling fractions \( f_h = n_h/N_h \) are small for the original without-replacement survey design. When the sampling fractions are not small, an ad hoc adjustment to (4) is to apply the finite population correction factor \( 1 - f_h \) within each stratum. The resulting variance estimator is given by

$$\hat{\text{Var}} = N^{-2} \left[ \frac{1 - f_h}{n_h(n_h-1)} \sum_{i_h \in S_h} \left( n_h w_{i_h} y_{i_h} - \sum_{i_h' \in S_h} w_{i_h'} y_{i_h} \right)^2 \right]. \quad (5)$$

The variance estimator \( \hat{\text{Var}} \) given in (5) is exactly design-unbiased for stratified simple random sampling. For general stratified unequal probability sampling, the performance of \( \hat{\text{Var}} \) varies depending on the original survey design. There exist other approximate variance formulas not involving second-order inclusion probabilities and performing better for certain designs. See, for instance, Haziza et al. (2008) for further details. The variance estimator \( \hat{\text{Var}} \) is the default option for most survey packages, including R, SAS, SPSS and Stata.

Stratified multi-stage sampling can use approximate variance estimators similar to \( \hat{\text{Var}} \) if sampling fractions for the first stage clusters are small within each stratum. For cases where \( N \) is unknown and the Hájek estimator \( \hat{\mu}_y \) is used, the variance estimator \( \hat{\text{Var}} \) given in (5) needs to be modified with \( \hat{N} \) being replaced by \( \hat{N} \) and the study variable \( y_{i_h} \) being substituted by the residual variable \( e_{i_h} = y_{i_h} - \hat{\mu}_{yHT} \) for computing the variance estimator. Further details can be found in Wu and Thompson (2020).

Regression analysis

Linear regression analysis and logistic regression analysis are commonly conducted by researchers in health sciences. Survey weighted regression analysis focuses on finite population regression coefficients and also provides valid results for the model parameters under the assumed regression model. For simplicity of notation, we assume that the covariates \( x \) contain 1 as the first component and the regression model has an intercept. The finite population regression coefficients \( \hat{\beta}_N \) are the solution to the so-called census estimating equations,

$$U_N(\hat{\beta}) = \sum_{h=1}^{H} \sum_{i_h=1}^{N_h} x_{i_h} \left( y_{i_h} - \mu(x_{i_h}, \beta) \right) = 0, \quad (6)$$
where $\mu(x_i; \beta) = E(y_i \mid x_i)$ is the mean function under the assumed regression model. For linear regression analysis, we have $\mu(x; \beta) = x' \beta$; for logistic regression analysis where $y$ is a binary variable, we have

$$\mu(x, \beta) = E(y \mid x) = P(y = 1 \mid x) = \frac{\exp(x' \beta)}{1 + \exp(x' \beta)}.$$ 

The survey weighted estimator of $\beta_N$, denoted as $\hat{\beta}_N$, is the solution to the survey weighted estimating equations,

$$\sum_{h=1}^{H} \sum_{i \in S_h} w_{ih} x_{ih} \{y_{ih} - \mu(x_{ih}; \beta)\} = 0. \tag{7}$$

Under the linear regression model, the estimator $\hat{\beta}_N$ has a closed form expression. Under the logistic regression model, it requires an iterative computational procedure to find the solution $\hat{\beta}_N$. The variance estimator for $\hat{\beta}_N$ is derived based on the theory of estimating equations and has the well-known sandwich form (Binder (1983)),

$$\text{Var}(\hat{\beta}_N) = \left\{ H_n(\hat{\beta}_N) \right\}^{-1} \tilde{V} \left\{ H_n(\hat{\beta}_N) \right\} \left\{ H_n(\hat{\beta}_N) \right\}^{-1}, \tag{8}$$

where $H_n(\beta) = \partial U_n(\beta)/\partial \beta$ and $\tilde{V}(U_n(\hat{\beta}_N))$ is the estimated variance-covariance matrix of the Horvitz-Thompson estimator $U_n(\beta) = \sum_{h=1}^{H} \sum_{i \in S_h} w_{ih} g_{ih}$ with $g_{ih} = x_{ih} \{y_{ih} - \mu(x_{ih}; \beta)\}$ and $\beta$ being replaced by $\hat{\beta}_N$ for enumerations. The variance estimator $\tilde{V}$ given in (5) is used again as the default option for most survey software packages on regression analysis. With the vector form of $g_{ih}$, the estimator of the variance-covariance matrix is given by

$$\tilde{V} \left\{ U_n(\hat{\beta}_N) \right\} = \sum_{h=1}^{H} \frac{1 - f_h}{n_h(n_h - 1)} \sum_{i \in S_h} \left( n_h w_{ih} g_{ih} - \sum_{i \in S} w_{ih} g_{ih} \right) \left( n_h w_{ih} g_{ih} - \sum_{i \in S} w_{ih} g_{ih} \right)' \tag{9}.$$ 

Chapter 7 of Wu and Thompson (2020) contains detailed discussions on regression analysis using survey data.

In survey sampling, estimation of regression coefficients or other parameters related to a model is often referred to as analytic use of survey data. It is apparent from the estimating equation system given in (7) and the sandwich variance estimator specified in (9) that rescaling the design weights $w_{ih}$ by a constant does not change the point estimator $\hat{\beta}_N$ or the variance estimator. Survey agencies sometimes provide the so-called analytic weights as part of the survey datasets. These weights are rescaled from the original design weights such that the sum of the analytic weights equals to the sample size.

3. Sampling design of the CLSA

The Canadian Longitudinal Study on Aging (CLSA) uses a stratified single-stage sampling design and has a large sample of 51,338 Canadian residents aged 45-85 years at baseline. Respondents in the initial sample are to be followed in subsequent survey waves for at least 20 years or until death or loss to follow-up. There are two types of respondents in the sample:

1. CLSA Tracking cohort, which has a target size of 20,000 people from across the 10 Canadian provinces;
2. CLSA Comprehensive cohort, which aims to have 30,000 people living within 25-50 km of one of the 11 Data Collection Sites (DCS) across 7 Canadian provinces.

Respondents in both cohorts are surveyed through telephone for a common set of baseline questions. Respondents in the comprehensive cohort are required to visit one of the DCSs to take additional measurements for key health related variables. Further details on the CLSA survey design and sampling procedures as well as measurements collected for each respondent can be found in Canadian Longitudinal Study on Aging (2011) and Raina et al. (2019).

The geographic variables are the stratum indicator variables for the original CLSA survey design. The variables are namely GEOSTRAT_TRM for the tracking cohorts, GEOSTRAT_COM for the comprehensive cohorts, and GEOSTRAT_CLSAM for the pooled dataset of both cohorts. Researchers may also consider to stratify further using gender, age groups, education level, etc. We do not consider stratification beyond the geographic variables in this paper.
4. Data preparation and survey design declaration

The demonstrations presented in this paper focus on the datasets from the CLSA. A comma-separated values (.csv) file is available for a CLSA dataset with the variable name provided in the first row. Steps for importing the dataset with different software packages are described below. The main dataset we use is from the tracking cohort with the strata variable \texttt{GEOSTRAT_TRM} as well as the survey weight variable, \texttt{WGHTS_INFLATION_TRM}.

**R preparation**

In R, the command \texttt{read.csv} is used for importing datasets from CSV files:

```r
CLSAData <- read.csv("[Path]/CLSARealExample.csv", header=TRUE, sep = ",")
```

Then, we can specify the age groups and declare the survey design with the package \texttt{survey}:

```r
library (survey)
CLSAData$StraVar <- CLSAData$GEOSTRAT_TRM
CLSADesign<- svydesign( ids= ~ entity_id, strata = ~ StraVar,
weights = ~ WGHTS_INFLATION_TRM, data= CLSAData, nest =TRUE )
```

The option \texttt{weights} specifies the sampling weights. We use the inflation weights for tracking cohort with name "\texttt{WGHTS_INFLATION_TRM}". The analyses of different cohorts would have different weight variables: for analysis involving comprehensive cohort, the label for the inflation weights is "\texttt{WGHTS_INFLATION_COM}"; for analysis involving combined cohort, the label for the inflation weights is "\texttt{WGHTS_INFLATION_CLSAM}"; and the label for the strata variable is "\texttt{GEOSTRAT_CLSAM}".

Most proprietary statistical packages would assume single PSU strata to have no contribution to the variance by default (Bruin (2011)). We would add the following option:

```r
options(survey.lonely.psu = "certainty")
```

which means the program will ignore the PSUs with single observations during variance calculation. If there is a stratum with only one sampled PSU, the program would ignore the stratum when computing the estimated variance. The option would not impact the results if all the strata have more than one sampled PSU.

**SAS preparation**

Here is how to import the CSV file as a SAS dataset. This step is skipped if one already has the CLSA datasets in SAS format. We do not need to declare the survey design at this stage as we will specify the design during data analysis.

```sas
PROC IMPORT datafile="[Path]/CLSARealExample.csv"
   out=CLSAData dbms=csv replace;
   GETNAMES=YES; DATAROW=2; guessingrows=max ;
RUN;
```

By default, SAS will ignore the PSUs with single observations during variance calculation.

**SPSS preparation**

In SPSS, readers can import the CLSA datasets by the user interface: "File" → "Import Data" → "CSV Data" → select the datafile and click "Open". Then follow the instruction on the screen and click "Ok".

To create the stratum variable, Transform → Compute Variable → Type "StraVar" under "Target Variable" and "WGHTS_GEOSTRAT_TRM" under "Numeric Expression" → click: "Type & Labels" and select "String" in the "Type" panel.

We then declare the survey design by clicking "Analyze" → Complex Samples → Prepare for Analysis → click "Create a plan file" and choose a location and name as CLSADesign.csaplan → "Next". Under Strata, select the variables "StraVar"and select "WGHTS_INFLATION_TRM" under "Sampling Weight" and accept the default settings.
By default, SPSS will ignore the PSUs with single observations during variance calculation.

**Stata preparation**

In Stata, we need to enter the following code to import the CSV file data:

```stata
import delimited [Path]/CLSARealExample.csv
```

To specify the sampling design, we define the stratum variables as `WGHTS_GEOSTRAT_TRM` and declare the survey design. Similar to the R program, we assume that strata with a single unit have no contribution to the variance estimation, so we put "certainty" in `singleunit()`."

```stata
generate StraVar = GEOSTRAT_TRM
svyset entity_id, strata(StraVar) weight(WGHTS_INFLATION_TRM) vce(linearized) singleunit(certainty)
```

The option "singleunit(certainty)" means the program will ignore the strata with single observations during variance calculation. Again, this option may not be the best one as it can underestimate the uncertainty.

**5. Estimation of descriptive population parameters**

We list several standard procedures of the complex survey data and compare the standard errors based on Taylor-series linearization across different packages.

**Estimation of frequencies**

The variable `ENV_AFRDWLK_MCQ` represents the CLSA survey question: "People would be afraid to walk alone after dark in this area." If we want to estimate the total number of people in the study population who agree or disagree about the statement, we can use the following sets of codes to create tables of frequencies with standard errors.

**R:**

```r
svytotal( ~(ENV_AFRDWLK_MCQ), design= CLSA.design)
```

**SAS:**

```sas
PROC SURVEYFREQ data= CLSAData ;
   TABLE ENV_AFRDWLK_MCQ1;
   strata GEOSTRAT_TRM ;
   weight WGHTS_INFLATION_TRM;
RUN;
```

**SPSS:**

Click "Analyze" → "Complex Samples" → "Frequency..." → Browse and select the CLSADesign.csaplan created. → Click "Next" and import a variable (ENV_AFRDWLK_MCQ) → Click "Statistics..." → select "Population size" and "Standard error" → Click "Continue" → Click "OK".

**Stata:**

```stata
svy linearized : tabulate ENV_AFRDWLK_MCQ, count se ci stubwidth(20) format(%10.0g)
```

**Results comparison**
### Estimation of population means

In CLSA, the variables `HWT_DHT_M_TRM` and `HWT_WGHT_KG_TRM` represent the self-reported body height (in meter) and body weight (in kilogram), respectively. To estimate the population averages of height and weight of the target population, we can apply the following sets of code to create tables of mean estimates with standard errors.

**R:**

\[
\text{svymean( ~ HWT_DHT_M_TRM+HWT_WGHT_KG_TRM , CLSA.design )}
\]

**SAS:**

```
PROC SURVEYMEANS data= CLSAData ;
TABLE ENV_AFRDWLK_MCQ1;
strata GEOSTRAT_TRM ;
weight WGHTS_INFLATION_TRM ;
RUN;
```

**SPSS:**

1. Click "Analyze" → "Complex Samples" → "Descriptive..." → Browse and select the "CLSADesign.csaplan" → Click "Continue" and enter variables "HWT_DHT_M_TRM" and "HWT_WGHT_KG_TRM" to the "Measures:" panel → click "Statistics..." → select "Mean" and "Standard error" → click "Continue" → click "OK".

**Stata:**

```
svy linearized : mean HWT_DHT_M_TRM HWT_WGHT_KG_TRM
```

### Results comparison

| Variable          | Estimate | R      | SAS     | SPSS    | Stata   |
|-------------------|----------|--------|---------|---------|---------|
| HWT_DHT_M_TRM     | Mean     | 1.6791 | 1.6791  | 1.6791  | 1.6791  |
|                   | SE       | 0.0037 | 0.0037  | 0.0037  | 0.0037  |
| HWT_WGHT_KG_TRM   | Mean     | 97.2682| 97.2682 | 97.2682 | 97.2682 |
|                   | SE       | 19.9207| 19.9207 | 19.9207 | 19.9207 |

### Estimation of ratios of population means

We created a variable `HWT_DHT_M_TRM_sq`, which is the square of the self-reported height (in meters). Suppose we want to estimate the ratio of the population mean of self-reported body weight and the population mean of self-reported boy height (squared), the estimate is computed as

\[
\frac{\sum_{i \in S} w_i(HWT_WGHT_KG_TRM_i)}{\sum_{i \in S} w_i(HWT_DHT_M_TRM_i)}
\]

where \( w_i \) is the survey weight and \( S \) is the set of sampled units.

### Note:

The total of the population estimates from the table above is much smaller than the CLSA study population. It is because the dataset used for illustration is only a subset of the CLSA dataset. The actual dataset should give much larger population totals.
R:

svyratio( numerator= ~HWT_WGHT_KG_TRM, denominator = ~ HWT_DHT_M_TRM_sq, design= CLSA.design )

SAS:

PROC SURVEYMEANS data= CLSAData ratio;
var HWT_WGHT_KG_TRM HWT_DHT_M_TRM_sq;
ratio HWT_WGHT_KG_TRM / HWT_DHT_M_TRM_sq ;
strata GEOSTRAT_TRM ;
weight WGHTS_INFLATION_TRM;
RUN;

SPSS:

Click "Analyze" → "Complex Samples" → "Ratios..." → Browse and select the "CLSA\text{Design.csaplan}" → Click "Continue" and enter variables "HWT\_WGHT\_KG\_TRM" and "HWT\_DHT\_M\_TRM\_sq" to the the "Numerators" and "Denominator" panels, respectively → Click "Statistics..." → Select "Standard error" → Click "Continue" → Click "OK".

Stata:

svy linearized : ratio (HWT_WGHT_KG_TRM/HWT_DHT_M_TRM_sq)

Results comparison

| Package | R    | SAS   | SPSS   | Stata   |
|---------|------|-------|--------|---------|
| Estimate| 34.4074 | 34.4074 | 34.4074 | 34.4074 |
| SE      | 7.0573 | 7.0573 | 7.0573 | 7.0573 |

Note: We need to be aware that the estimate of the ratio of two population means is conceptually different from the estimate of the population mean of the ratio of two variables. For the example discussed in this section, the latter is the estimate of the population mean of BMI and is given by

$$\sum_{i \in S} \frac{w_i HWT\_WGHT\_KG\_TRM_i}{HWT\_DHT\_M\_TRM\_sq_i}.$$

Estimation of population quantiles

Let $F_q(t) = N^{-1} \sum_{h=1}^{H} \sum_{i=1}^{N_h} I(y_{hi} \leq t)$ be the finite population distribution function, where $I(\cdot)$ is the indicator function. The 100\(p\)th population quantile with $p \in (0, 1)$ is defined as

$$Q(p) = F_q^{-1}(p) = \inf\{t \mid F_q(t) \geq p\}.$$

Suppose we want to estimate the population quantiles of the self-reported body weight and body height (HWT\_WGHT\_KG\_TRM, HWT\_DHT\_M\_TRM). The population median corresponds to the 50\% quantile. The following codes can be used.

R:

Quant.Est<-svyquantile( ~ HWT\_DHT\_M\_TRM\_sq+HWT\_WGHT\_KG\_TRM ,
quintile=c(0.025, 0.05, 0.1, 0.5, 0.9, 0.95, 0.975),
alpha=0.05, interval.type="Wald", design= CLSA\_design,
ties=c("rounded"), ci= TRUE, se=TRUE )
Quant.Est; SE(Quant.Est);
SAS:

```sas
PROC SURVEYMEANS data= CLSAData QUANTILE= (0.025 0.05 0.1 0.5 0.9 0.95 0.975) NOSYMCL;
VAR HWT_DHT_M_TRM HWT_WGHT_KG_TRM;
STRATA GEOSTRAT_TRM;
WEIGHT WGHTS_INFLATION_TRM;
RUN;
```

There is no formal procedure available to produce quantile estimates and their standard errors in the SPSS and Stata packages.

**Results comparison**

| Quantile | HWT_DHT_M_TRM | HWT_WGHT_KG_TRM | R | SAS | R | SAS |
|----------|---------------|-----------------|---|-----|---|-----|
| Estimate |               |                 |   |      |   |      |
| 0.025    | 1.5125        | 1.5125          | 50.0447 | 50.0447 | 1.0307 | 1.0311 |
| 0.05     | 1.5311        | 1.5311          | 53.1131 | 53.1131 | 1.6637 | 1.6637 |
| 0.1      | 1.5552        | 1.5552          | 56.4540 | 56.4540 | 1.7859 | 1.7859 |
| 0.5      | 1.6637        | 1.6637          | 75.4911 | 75.4911 | 1.8164 | 1.8164 |
| 0.9      | 1.7859        | 1.7859          | 96.7621 | 96.7621 | 1.8443 | 1.8443 |
| 0.95     | 1.8164        | 1.8164          | 107.0132| 107.0132| 1.8443 | 1.8443 |
| 0.975    | 1.8443        | 1.8443          | 116.2338| 116.2338| 1.8443 | 1.8443 |

For the standard error (SE) estimation, both R and SAS first construct 95% confident intervals (CIs) by the Woodruff’s method (Woodruff 1952), and then compute the standard errors from the division of the CI lengths by \( t_{df,0.025} \), the 97.50th percentile of the \( t \) distribution with degrees of freedom, \( df \), which is determined by the survey data and the survey design. For CLSA, the degrees of freedom is the number of observations minus the number of strata. If the sample size is relatively large, we can simply replace \( t_{df,0.025} \) by \( z_{0.025} \), the 97.50th percentile from the standard normal distribution.

The difference in standard errors is due to different implementation of Woodruff interval. Let \( y_1 \leq y_2 \leq \cdots \leq y_n \) denote the sample order statistics for the variable \( Y \). The 100th population quantile estimate is computed as

\[
\hat{Q}(p) = \begin{cases} 
  y(k) & \text{if } p \leq \hat{F}_Y(y(k)) \\
  y(k+1) - \hat{F}_Y(y(k)) & \text{if } \hat{F}_Y(y(k)) < p \leq \hat{F}_Y(y(k+1)) 
\end{cases}
\]

where \( \hat{F}_Y(t) = \sum_{i=1}^{n} I_{Y_{hi}} \leq t \) is the estimated cumulative distribution function for \( Y \) and \( \hat{N} = \sum_{i=1}^{n} I_{Y_{hi}} \leq t \) is the estimated cumulative distribution function for the population. The CI for 100th quantile can be obtained as \( (\hat{Q}(\hat{p}_L), \hat{Q}(\hat{p}_U)) \). In R, \( \hat{p}_L \) and \( \hat{p}_U \) are implemented as

\[
(\hat{p}_L, \hat{p}_U) = \left( p - t_{df,a/2} \sqrt{\hat{V}(\hat{F}_Y(\hat{Q}(p)))}, p + t_{df,a/2} \sqrt{\hat{V}(\hat{F}_Y(\hat{Q}(p)))} \right),
\]

while in SAS, \( \hat{p}_L \) and \( \hat{p}_U \) are implemented as

\[
(\hat{p}_L, \hat{p}_U) = \left( \hat{F}_Y(\hat{Q}(p)) - t_{df,a/2} \sqrt{\hat{V}(\hat{F}_Y(\hat{Q}(p)))}, \hat{F}_Y(\hat{Q}(p)) + t_{df,a/2} \sqrt{\hat{V}(\hat{F}_Y(\hat{Q}(p)))} \right),
\]

which explains the differences in the SE estimates.

One can observe that standard errors for the extreme quantiles are usually larger while the errors are smaller for quantiles around the median. This is because the data are sparser around the extreme quantiles and the sampling distributions of extreme quantile estimators are often skewed.
Estimation of odds ratios, relative risks and risk differences

Suppose we want to describe the population relationship between two binary variables, say whether experiencing dry mouth in the past 12 months (the variable ORH_EXP_DRM_MCQ) and sex (the variable SEX_ASK_TRM). The following codes can be used to produce estimates of odds ratios, relative risks and risk differences.

**R** There is no formal support from the R survey package to produce unadjusted odds ratios, relative risks, risk differences, nor the related confidence intervals. For the relative risk, there is only one example on page 103 of the manual of R survey (Lumley 2018). The following R codes can produce results similar to other survey packages.

```r
LogisticReg4.OR<-svyglm(ORH_EXP_DRM_MCQ ~ SEX_ASK_TRM,
                          family=quasibinomial(link="logit"),
                          design=CLSA.design)
exp(coef(LogisticReg4.OR)[2]) ## odds ratio
exp(confint(LogisticReg4.OR)[2,]) ## confidence interval

LogisticReg4.RR<-svyglm(ORH_EXP_DRM_MCQ ~ SEX_ASK_TRM,
                        family=quasibinomial(link="log"),
                        design=CLSA.design)
exp(coef(LogisticReg4.RR)[2]) ## relative risk
exp(confint(LogisticReg4.RR)[2,]) ## confidence interval

LogisticReg4.RD<-svyglm(ORH_EXP_DRM_MCQ ~ SEX_ASK_TRM,
                        family=quasibinomial(link="identity"),
                        design=CLSA.design)
coef(LogisticReg4.RD)[2] ## risk difference
confint(LogisticReg4.RD)[2,] ## Confidence interval
```

**SAS** We can obtain the unadjusted odds ratios, relative risks and risk differences by specifying the options, OR and RISK in the table statement. We can specify the order of the categorical variables by the Proc Format. Usually, SAS only provide confidence intervals instead of standard errors for the estimates.

```
PROC Format;
   VALUE Bin 1 = "1:Yes" 0 = "2:No" ;
   VALUE $genB "F" = "2:Female" "M" = "1:Male";
run;
PROC SURVEYFREQ data=CLSAData ORDER= FORMATTED ;
   TABLE SEX_ASK_TRM * ORH_EXP_DRM_MCQ / OR RISK ;
   STRATA GEOSTRAT_TRM;
   WEIGHT WGHTS_INFLATION_TRM;
   format ORH_EXP_DRM_MCQ Bin. SEX_ASK_TRM $genB. ;
RUN;
```

**SPSS** Analyze → Complex Samples → Crosstabs... → Select the file "CLSADesign.csaplan" in the Plan panel → click "Continue" → select the corresponding variables to the "Rows", "Factor" and target variable to the "Column" panels → click "Statistics..." → select "Confidence interval" and "Standard error" → click "Odds Ratios", "Risk difference" and "Relative risk" → click "Continue" → click "OK".

**Stata** There is no formal support from Stata survey package to produce unadjusted odds ratios, relative risks and risk differences and the confidence limits. However, the following codes can produce results similar to other survey packages.

```
Odds ratio:
svy linearized: logistic ORH_EXP_DRM_MCQ SEX_ASK_TRM
svy linearized: glm ORH_EXP_DRM_MCQ SEX_ASK_TRM, fam(binomial) link(log) eform
svy linearized: glm ORH_EXP_DRM_MCQ SEX_ASK_TRM, fam(binomial) link(identity)
```

**Results comparison**
### Note
The estimates of odds ratios, relative risks and risk differences obtained by these procedures describe the relationship of the target variables and exposure groups in the population. The binomial regressions used here do not describe a model for the variables in the population. Thus, the results in this section may be different from the logistics regression results in the later session. The reason is due to the use of “analytic weights”, which are often rescaled within each stratum under stratified sampling.

### Estimation of covariance
If we are interested in estimating the population variance and population covariance of the self-reported body height and body weight (HWT_DHT_M_TRM and HWT_WGHT_KG_TRM), the following codes can be used.

**R**

```r
print(svyvar(~ HWT_DHT_M_TRM+HWT_WGHT_KG_TRM, CLSA.design), covariance=TRUE)
```

**Result**

| Statistics                  | Estimate   | SE       |
|-----------------------------|------------|----------|
| Var (HWT_DHT_M_TRM)        | 7.5974E-03 | 4.0000E-04 |
| Var (HWT_WGHT_KG_TRM)      | 1.5382E+05 | 1.5246E+05 |
| Cov (HWT_DHT_M_TRM, HWT_WGHT_KG_TRM) | -1.3799E+00 | 2.0704E+00 |

**Note 1:** There are no formal procedures for estimation of population variance and covariance in SAS, SPSS or Stata.

**Note 2:** The population covariance is a descriptive parameter on the relationship between the two target variables in the population. Estimation of a population covariance is a different task than regression analysis to be presented in the next section.

### 6. Analytic weights and estimation of model parameters

Analytic use of survey data on estimation of model parameters has been discussed briefly in Section 2. The analytic weights, which are rescaled from the design weights (or inflation weights) with sum equaling to the sample size, are often used. They produce the same point estimates and variance estimates under non-stratified sampling. Under stratified sampling where strata have very different sizes, units in some large strata, such as the province of Ontario in the CLSA datasets, have much larger weights and observations from these large strata often dominate the analysis (Scott (2006); Thompson (2008)). A common practice in creating analytic weights under stratified sampling is to rescale the weights within each stratum such that the total stratum weight equals to the stratum sample size. The resulting estimates of the model parameters are not identical to the estimates using the inflation weights but are more stable and also interpretable for the given finite population (Thompson (2008)).

The analytic weights of the CLSA datasets are provided with the names WGHTS_ANALYTIC_***. For the datasets from the tracking cohort, the weights are given by the variable WGHTS_ANALYTIC_TRM and are proportional to the inflation weights but rescaled to sum to the sample size within each
province so that their mean value is one within each province. For the datasets from the comprehensive cohort, the weights are given by the variable WHTS_ANALYTIC_COM and are proportional to the inflation weights but rescaled to sum to sample size within the Data Collection Site (DCS) part of each province, so that their mean value is one within that area. For the datasets from the pooled data, the weights WHTS_ANALYTIC_CLSAM are proportional to the inflation weights for the pooled data but rescaled to sum to sample size within the DCS and non-DCS part of each province. Details of the analytic weights in other datasets are provided in the CLSA technical document on sample weights (Canadian Longitudinal Study on Aging 2011).

The survey design can be declared similarly as in Section 4 except replacing the survey weight with WHTS_ANALYTIC_TRM.

**For R:**

```r
CLSA.design.anly<- svydesign( ids= ~ entity_id, strata = ~ StraVar, weights = ~ WHTS_ANALYTIC_TRM, data= CLSAData, nest =TRUE )
```

**For SPSS:** We declare the survey design by clicking "Analyze" → Complex Samples → Prepare for Analysis → click "Create a plan file" and choose a location and name as CLSADesignAny1.csaplan → "Next". Under Strata, select the variables "StraVar" and select "WGHT_ANALYTIC_TRM" under "Sampling Weight" and accept the default settings.

**For Stata:**

```stata
svyset entity_id, strata(StraVar) weight(WGHTS_ANALYTIC_TRM) vce(linearized) singleunit(certainty)
```

**Comments on the selection of variables for analysis**

It is recommended that key design variables for CLSA, such as gender, age group (45-54, 55-64, 65-74, and 75-85), education level (low, medium, high lower, and high upper), should be included in the initial model. The stratum indicator variables, i.e., the provinces for the tracking cohort or the provinces crossed with individual DCS areas for the comprehensive cohort and the pooled cohorts, may also be included. Some of these variables may be removed in the final model if it is shown that they are not significant.

**Linear regression analysis**

We consider a regression model with the self-reported body height as the response variable and the body weight as the key predictor. We also include province, sex, age group, and education level in the initial model.

**R:**

```r
LinearReg<-svyglm( HWT_DHT_M_TRM~ HWT_WGHT_KG_TRM+WGHTS_PROV_TRM1 + SEX_ASK_TRM + Age_Grp+Education, family="gaussian", design=CLSA.design.anly) summary(LinearReg)
```

**SAS:**

```sas
PROC SURVEYREG data=CLSAData order=formatted;
CLASS WHTS_PROV_TRM1 Age_Grp SEX_ASK_TRM Education ;
STRATA GEOSTRAT_TRM ;
MODEL HWT_DHT_M_TRM = HWT_WGHT_KG_TRM WHTS_PROV_TRM1 SEX_ASK_TRM Age_Grp Education / solution ;
WEIGHT WHTS_ANALYTIC_TRM;
STORE out=LinearReg;
ods output ParameterEstimates = MyParmEst ;
RUN;
PROC print data =MyParmEst;
FORMAT Estimate 10.9 StdErr10.9;
RUN;
```
SPSS:

Analyze \rightarrow Complex Samples \rightarrow General Linear Model... \rightarrow Select the file "CLSADesignAnyl.csaplan" in the Plan panel \rightarrow click "Continue" \rightarrow select the corresponding variables to the 'Dependent Variable', 'Factor' and 'Covariate' panels \rightarrow click "Statistics..." \rightarrow select "Estimate" and "Standard error" \rightarrow click "Continue" \rightarrow click "Save" \rightarrow click enter the path and file name "LinearReg.xml" under "Export Model as XML" \rightarrow click "Continue" \rightarrow Click "Finish".

Stata:

svy linearized : regress HWT_DHT_M_TRM HWT_WGHT_KG_TRM i.WGHTS_PROV_TRM SEX_ASK_TRM i.Age_GRP i.Education
estimates save "[Path]\LinearReg.ster", replace

Results comparison:

| Population Est. | R         | SAS        | SPSS        | Stata        |
|-----------------|-----------|------------|-------------|--------------|
| (Intercept)     | 1.6188    | 1.6188     | 1.6188      | 1.6188       |
| HWT_WGHT_KG_TRM| -6.34E-6  | -6.34E-6   | -6.34E-6    | -6.34E-6     |
| SEX_ASK_TRM     | 0.1247    | 0.1247     | 0.1247      | 0.1247       |
| Age Groups      |           |            |             |              |
| (rel. to Age_GRP1: Age 45-54) | 0.0059   | 0.0059     | 0.0059      | 0.0059       |
| Age_GRP2:Age 55-64 | -0.0292 | -0.0292    | -0.0292     | -0.0292      |
| Age_GRP3:Age 65-74 | -0.0135 | -0.0135    | -0.0135     | -0.0135      |
| Age_GRP4:Age 75+ |           |            |             |              |
| Education Levels|           |            |             |              |
| (rel. to Lower Education) | 0.0056   | 0.0056     | 0.0056      | 0.0056       |
| Higher Education lower | 0.0094  | 0.0094     | 0.0094      | 0.0094       |
| Higher Education upper | 0.0186 | 0.0186     | 0.0186      | 0.0186       |
| Provinces       |           |            |             |              |
| (rel. to Alberta) |         |            |             |              |
| British Columbia | 0.0131  | 0.0131     | 0.0131      | 0.0131       |
| Manitoba        | 0.0073   | 0.0073     | 0.0073      | 0.0073       |
| New Brunswick   | -0.0040  | -0.0040    | -0.0040     | -0.0040      |
| Newfoundland & Labrador | 0.0005 | 0.0005     | 0.0005      | 0.0005       |
| Nova Scotia     | 0.0055   | 0.0055     | 0.0055      | 0.0055       |
| Ontario         | -0.0015  | -0.0015    | -0.0015     | -0.0015      |
| Prince Edward Island | -0.0056 | -0.0056    | -0.0056     | -0.0056      |
| Quebec          | -0.0100  | -0.0100    | -0.0100     | -0.0100      |
| Saskatchewan    | -0.0136  | -0.0136    | -0.0136     | -0.0136      |

The fitted model can be used to predict the response at a new data entry. We take the first entry of the dataset as an example for illustration and compare the predicted height and confidence intervals.

R:

Pred1 <- predict(LinearReg, newdata= CLSAData[1,], se.fit=TRUE)
Pred1; confint(Pred1)

SAS:

PROC plm source=LinearReg ALPHA=0.05;
score data=CLSAData(obs=1) out=testout predicted STDERR LCLM UCLM / ilink;
run;

PROC print data=testout;
VAR predicted STDERR LCLM UCLM;
format predicted 10.9 STDERR 10.9 LCLM 10.9 UCLM 10.9;
run;

SPSS: Open a new dataset \rightarrow Utilities \rightarrow Scoring Wizard \rightarrow Click "Browse" and enter the corresponding path and select "LinearReg.xml" \rightarrow Click "Next >" \rightarrow Match the variable with model fields \rightarrow Click "Next >" \rightarrow Click "Finish".
Stata:

estimates use "[Path]\LinearReg.ster"
predict p1 if entity_id == 39511 , xb
predict se1 if entity_id == 39511 , stdp
display p1
display se1
display p1 - invnormal(0.975)*se1
display p1 + invnormal(0.975)*se1

Results comparison:

|                      | R       | SAS      | SPSS     | Stata    |
|----------------------|---------|----------|----------|----------|
| Predicted value      | 1.6280  | 1.6280   | 1.6280   | 1.6280   |
| Standard error       | 0.0108  | 0.0109   | 0.0108   | 0.0108   |
| 95% Lower confidence limit | 1.6068  | 1.6066   | Not provided | 1.6068 |
| 95% Upper confidence limit | 1.6492  | 1.6494   | Not provided | 1.6492 |

Logistic regression analysis

In the CLSA datasets, the variable "ORH_EXP_DRM_MCQ" indicates if the respondents experienced dry mouth in the last 12 months. We relate this variable to the age group of the respondents through a logistic regression model. The variables sex, province and education level are also included in the initial model as covariates.

R:

```R
LogitReg<-svyglm( ORH_EXP_DRM_MCQ ~ WGHTS_PROV_TRM1 + SEX_ASK_TRM + Age_Grp+Education, family=quasibinomial,design=CLSA.design.anly)
summary(LogitReg)
```

SAS:

```SAS
PROC SURVEYLOGISTIC data=CLSAData ;
class ORH_EXP_DRM_MCQ(ref=first) WGHTS_PROV_TRM1 Age_Grp SEX_ASK_TRM Education/param=ref;
model ORH_EXP_DRM_MCQ (event='1')= WGHTS_PROV_TRM1 Age_Grp SEX_ASK_TRM Education;
strata GEOSTRAT_TRM;
weight WGHTS_ANALYTIC_TRM;
store out= LogitReg;
ods output ParameterEstimates = MyParmEst;
RUN;
PROC print data = MyParmEst;
format Estimate 10.9 StdErr 10.9;
run;
```

SPSS:

```
Analyze → Complex Samples → Logistic Regression... → Select the file "CLSADesignAnyL.cspplan" in the Plan panel → click "Continue" → select the corresponding variables to the 'Dependent Variable', 'Factor' and 'Covariate' panels → click 'Reference Category' and select 'Lowest value' → click "Statistics..." → select 'Estimate' and 'Standard error' → click 'Continue' → Click 'Save...' → Enter "LogitReg.xml" under 'Export Model as XML' → click 'Continue' → click "OK".
```

Stata:

```
svy linearized: logit ORH_EXP_DRM_MCQ i.WGHTS_PROV_TRM SEX_ASK_TRM i.Age_Grp i.Education
estimates save "[Path]\LogitReg.ster", replace
```
Results comparison:

| Population Est.      | R             | SAS           | SPSS          | Stata          |
|-----------------------|---------------|---------------|---------------|---------------|
| (Intercept)           | -1.0106 0.5382| -1.0106 0.5435| -1.0106 0.5378| -1.0106 0.5382|
| SEX_ASK_TRMM          | -0.5274 0.2055| -0.5274 0.2076| -0.5274 0.2054| -0.5274 0.2055|
| Age Groups (rel. to Age_Gpr1: Age 45-54) | | | | |
| Age_Gpr2:Age 55-64   | 0.3921 0.3335 | 0.3921 0.3369 | 0.3921 0.3334 | 0.3921 0.3335 |
| Age_Gpr3:Age 65-74   | 0.7467 0.3325 | 0.7467 0.3358 | 0.7467 0.3326 | 0.7467 0.3325 |
| Age_Gpr4:Age 75+     | 0.8633 0.4467 | 0.8633 0.4511 | 0.8633 0.4464 | 0.8633 0.4467 |
| Education Levels (rel. to Lower Education) | | | | |
| Medium Education      | -0.1388 0.3414 | -0.1388 0.3448 | -0.1388 0.3422 | -0.1388 0.3414 |
| Higher Education lower| -0.0473 0.3428 | -0.0473 0.3462 | -0.0473 0.3432 | -0.0473 0.3428 |
| Higher Education upper| -0.1112 0.3420 | -0.1112 0.3455 | -0.1112 0.3422 | -0.1112 0.3420 |
| Provinces (rel. to Alberta) | | | | |
| British Columbia     | -0.9356 0.4639 | -0.9356 0.4686 | -0.9356 0.4639 | -0.9356 0.4639 |
| Manitoba             | -0.2682 0.4478 | -0.2682 0.4522 | -0.2682 0.4478 | -0.2682 0.4478 |
| New Brunswick        | -0.0187 0.4500 | -0.0187 0.4545 | -0.0187 0.4500 | -0.0187 0.4500 |
| Newfoundland & Labrador | -0.4196 0.4767 | -0.4196 0.4815 | -0.4196 0.4731 | -0.4196 0.4767 |
| Nova Scotia          | 0.3213 0.4541 | 0.3213 0.4586 | 0.3213 0.4541 | 0.3213 0.4541 |
| Ontario              | -0.2506 0.4268 | -0.2506 0.4311 | -0.2506 0.4268 | -0.2506 0.4268 |
| Prince Edward Island | -0.4300 0.4818 | -0.4300 0.4866 | -0.4300 0.4818 | -0.4300 0.4818 |
| Quebec               | -0.4541 0.3862 | -0.4541 0.3901 | -0.4541 0.3862 | -0.4541 0.3862 |
| Saskatchewan         | -0.6365 0.4915 | -0.6365 0.4964 | -0.6365 0.4914 | -0.6365 0.4914 |

The fitted model can also be used to predict the probabilities of the response categories at a new data entry. We take the first entry of the dataset as an example for illustration and compare the predicted probability of "YES" and confidence intervals.

R:
```
Pred2<- predict( LogitReg, newdata= CLSAData[1,], type= "link", se.fit=TRUE)
plogis(Pred2[1]); plogis(confint(Pred2))
predict( LogitReg, newdata= CLSAData[1,], type= "response", se.fit=TRUE) # for SE
```

SAS:
```
PROC plm source=LogitReg ALPHA=0.05 ;
score data=CLSAData(obs=1) out=testout predicted STDERR LCLM UCLM / ilink;
run;
PROC print data=testout;
VAR predicted STDERR LCLM UCLM ;
format predicted 10.9 STDERR 10.9 LCLM 10.9 UCLM 10.9;
run;
```

SPSS:
```
Open a new dataset → Utilities → Scoring Wizard → Click "Browse" and enter the corresponding path and select "LogitReg.xml" → Click "Next >" → Match the variable with model fields → Click "Next >" → Enter a value for selected probability → Click "Next >" and Click "Finish".
```

Stata:
```
estimates use "[Path]\LogitReg.ster"
predict p2 if entity_id == 39511 , xb
predict se2 if entity_id == 39511 , stdp
display invlogit(p2)
display invlogit(p2 - invnormal(0.975)*se2)
display invlogit(p2 + invnormal(0.975)*se2)
```
Results comparison:

|                | R  | SAS | SPSS       | Stata |
|----------------|----|-----|------------|-------|
| Predicted value| 0.2505 | 0.2505 | 0.2505     | 0.2505 |
| Standard error | 0.0734 | 0.0741 | Not provided | Not provided |
| 95% Lower confidence limit | 0.1336 | 0.1375 | Not provided | 0.1345 |
| 95% Upper confidence limit | 0.3944 | 0.4201 | Not provided | 0.4183 |

Multinomial logistic regression analysis

Multinomial logistic regression deals with nominal responses with three or more categories. Suppose we want to investigate the relationship between current marital statuses WEA_MRTL_CURRENT_MCQ and sex, age group, education level and province. We can use a multinomial logistic regression model with the following codes.

**R:** There is no official support for multinomial regression from the R package `survey`.

**SAS:**

```
PROC SURVEYLOGISTIC data=CLSAData;
class WEA_MRTL_CURRENT_MCQ2 SEX_ASK_TRM Age_Grp Education WGHTS_PROV_TRM /param=ref;
model WEA_MRTL_CURRENT_MCQ2 = SEX_ASK_TRM Age_Grp Education WGHTS_PROV_TRM /link=glogit;
strata GEOSTRAT_TRM;
weight WGHTS_ANALYTIC_TRM;
RUN;
```

**SPSS:**

Analyze → Complex Samples → Logistic Regression... → Select the file "CLSADesignAny1.casplan" in the Plan panel → click "Continue" → select the corresponding variables to the "Dependent Variable", "Factor" and "Covariate" panels → click "Reference Category" and select "Lowest value" → click "Statistics..." → select "Estimate" and "Standard error" → click "Continue" → click "OK".

**Stata:**

```
svy linearized: mlogit WEA_MRTL_CURRENT_MCQ1 SEX_ASK_TRM i.Age_Grp i.Education
   i.WGHTS_PROV_TRM , baseoutcome(1)
```

Results comparison:
### Ordinal logistic regression analysis

Many variables in complex surveys are ordinal, where the response variable has a well-defined order for the categories. Ordinal logistic regression analysis is suitable to model the relationship between the probabilities of the cumulative categories and the key factors. Suppose we are interested in the relationship between the response categories of `ENV_AFRDWLK_MCQ`: Strongly Agree $(d = 1)$, Agree $(d = 2)$, Disagree $(d = 3)$, and Strongly Disagree$(d = 4)$ and sex and age. The cumulative logistic regression model has the form

$$g(Pr(Y < d \mid x)) = \alpha_d + x' \beta, \quad \text{(for SAS)}$$

$$g(Pr(Y < d \mid x)) = \alpha_d - x' \eta, \quad \text{(for R, SPSS and Stata)}$$

with $d = 2, 3, 4$, where $g(\cdot)$ is a link function. We usually specify $g(\cdot)$ as the logit function, and the model becomes the cumulative logit model (also known as the proportional odds model). For comparison purposes, we multiply $–1$ to the SAS coefficient estimates output for $\beta$.

---

### Table: Coefficient Estimates

| (relative to 1:Single) | Coefficient | Est. | SE  | Est. | SE  | Est. | SE  |
|------------------------|-------------|------|-----|------|-----|------|-----|
| 2: Married             |             |      |     |      |     |      |     |
| (Intercept)            | 1.8405      | 0.7732 | 1.8404 | 0.7578 | 1.8404 | 0.7578 |
| SEX_ASK_TRMM           | 0.3545      | 0.3015 | 0.3545 | 0.2955 | 0.3545 | 0.2955 |
| Age Groups             |             |      |     |      |     |      |     |
| (rel. to Age_Gpr1: Age 45-54) |    |      |     |      |     |      |     |
| Age_Gpr2: Age 55-64    | 0.2326      | 0.4226 | 0.2326 | 0.4142 | 0.2326 | 0.4142 |
| Age_Gpr3: Age 65-74    | 0.2151      | 0.4512 | 0.2151 | 0.4422 | 0.2151 | 0.4422 |
| Age_Gpr4: Age 75+      | -0.6337     | 0.6108 | -0.6337 | 0.5986 | -0.6337 | 0.5986 |
| Education Levels       |             |      |     |      |     |      |     |
| (rel. to Lower Education) |           |      |     |      |     |      |     |
| Medium Education       | 0.1864      | 0.5388 | 0.1864 | 0.5281 | 0.1864 | 0.5281 |
| Higher Education lower | 0.1275      | 0.5510 | 0.1275 | 0.5400 | 0.1275 | 0.5400 |
| Higher Education upper | 0.3125      | 0.5393 | 0.3125 | 0.5286 | 0.3125 | 0.5286 |
| Provinces              |             |      |     |      |     |      |     |
| (rel. to Alberta)      |             |      |     |      |     |      |     |
| British Columbia       | -0.0696     | 0.6455 | -0.0696 | 0.6326 | -0.0696 | 0.6326 |
| Manitoba               | -0.5858     | 0.5732 | -0.5858 | 0.5637 | -0.5858 | 0.5637 |
| New Brunswick          | 0.5804      | 0.7378 | 0.5804 | 0.7231 | 0.5804 | 0.7231 |
| Newfoundland & Labrador | -0.0135  | 0.7509 | -0.0135 | 0.7359 | -0.0135 | 0.7359 |
| Nova Scotia            | 0.3114      | 0.7195 | 0.3114 | 0.7052 | 0.3114 | 0.7052 |
| Ontario                | -0.5085     | 0.5857 | -0.5085 | 0.5739 | -0.5085 | 0.5739 |
| Prince Edward Island   | -1.2410     | 0.6086 | -1.2410 | 0.5964 | -1.2410 | 0.5964 |
| Quebec                 | -0.8317     | 0.5443 | -0.8317 | 0.5334 | -0.8317 | 0.5334 |
| Saskatchewan           | 1.6674      | 1.1595 | 1.6690 | 1.1378 | 1.6690 | 1.1378 |
| 3: Others              |             |      |     |      |     |      |     |
| (Intercept)            | 0.1472      | 0.9537 | 0.1472 | 0.9347 | 0.1472 | 0.9347 |
| SEX_ASK_TRMM           | -0.8986     | 0.3528 | -0.8986 | 0.3457 | -0.8986 | 0.3457 |
| Age Groups             |             |      |     |      |     |      |     |
| (rel. to Age_Gpr1: Age 45-54) |    |      |     |      |     |      |     |
| Age_Gpr2: Age 55-64    | 0.9486      | 0.5433 | 0.9486 | 0.5325 | 0.9486 | 0.5325 |
| Age_Gpr3: Age 65-74    | 1.2005      | 0.5663 | 1.2005 | 0.5550 | 1.2005 | 0.5550 |
| Age_Gpr4: Age 75+      | 1.5612      | 0.6868 | 1.5612 | 0.6731 | 1.5612 | 0.6731 |
| Education Levels       |             |      |     |      |     |      |     |
| (rel. to Lower Education) |           |      |     |      |     |      |     |
| Medium Education       | 0.4234      | 0.6150 | 0.4234 | 0.6027 | 0.4234 | 0.6027 |
| Higher Education lower | 0.2592      | 0.6259 | 0.2592 | 0.6134 | 0.2592 | 0.6134 |
| Higher Education upper | 0.3732      | 0.6256 | 0.3732 | 0.6131 | 0.3732 | 0.6131 |
| Provinces              |             |      |     |      |     |      |     |
| (rel. to Alberta)      |             |      |     |      |     |      |     |
| British Columbia       | -0.3919     | 0.7073 | -0.3919 | 0.6932 | -0.3919 | 0.6932 |
| Manitoba               | -0.4276     | 0.6639 | -0.4276 | 0.6506 | -0.4276 | 0.6506 |
| New Brunswick          | 0.3460      | 0.8432 | 0.3460 | 0.8264 | 0.3460 | 0.8264 |
| Newfoundland & Labrador | -0.9291  | 0.8419 | -0.9291 | 0.8251 | -0.9291 | 0.8251 |
| Nova Scotia            | 0.2144      | 0.7987 | 0.2144 | 0.7827 | 0.2144 | 0.7827 |
| Ontario                | -0.7852     | 0.6684 | -0.7852 | 0.6551 | -0.7852 | 0.6551 |
| Prince Edward Island   | -1.3250     | 0.7084 | -1.3250 | 0.6943 | -1.3250 | 0.6943 |
| Quebec                 | -0.6610     | 0.6208 | -0.6610 | 0.6084 | -0.6610 | 0.6084 |
| Saskatchewan           | 1.1766      | 1.2168 | 1.1781 | 1.1939 | 1.1781 | 1.1939 |
summary(svyolr(formula = ENV_AFRDWLK_MCQ2 ~ SEX_ASK_TRM + Age_Grp+ Education+WGHTS_PROV_TRM, design = CLSA.design.anly, na.action = na.omit, method = c("logistic")) )

SAS:
PROC surveylogistic data=CLSAData ;
class ENV_AFRDWLK_MCQ2(ref=first) /param=ref;
model ENV_AFRDWLK_MCQ2 = SEX_ASK_TRM Age_Grp Education WGHTS_PROV_TRM /clodds ;
strata GEOSTRAT_TRM;
weight WGHTS_ANALYTIC_TRM;
run;

SPSS:
Analyze → Complex Samples → Ordinal Regression... → Select the file "CLSADesignAny1.casplan" in the Plan panel → click "Continue" → select the corresponding variables to the "Dependent Variable", "Factor" and "Covariate" panels → click "Response Probabilities" and select "Accumulate from lowest value of dependent variable to highest value" → click "Statistics..." → select "Estimate" and "Standard error" → click "Continue" → click "OK".

Stata:
svy linearized : ologit ENV_AFRDWLK_MCQ2 SEX_ASK_TRM i.Age_Grp i.Education i.WGHTS_PROV_TRM

Results comparison:

| Population Est. | R     | SAS           | SPSS          | Stata         |
|-----------------|-------|---------------|---------------|---------------|
| SEX_ASK_TRM     | 0.1858 | 0.1640        | 0.1858        | 0.1858        |
| Age Groups      |       |               |               |               |
| (rel. to Age_Gpr1: Age 45-54) |       |               |               |               |
| Age_Gpr2:Age 55-64 | 0.0222 | 0.2625        | 0.0222        | 0.0222        |
| Age_Gpr3:Age 65-74 | -0.3018 | -0.3017       | -0.3018       | -0.3018       |
| Age_Gpr4:Age 75+ | -1.1128 | -1.1128       | -1.1128       | -1.1128       |
| Education Levels|       |               |               |               |
| (rel. to Lower Education) |       |               |               |               |
| Medium Education | -0.0050 | -0.0053       | -0.0050       | -0.0050       |
| Higher Education lower | -0.0676 | -0.0679       | -0.0676       | -0.0676       |
| Higher Education upper | 0.4452 | 0.4448        | 0.4452        | 0.4452        |
| Provinces      |       |               |               |               |
| (rel. to Alberta) |       |               |               |               |
| British Columbia | 0.0051 | 0.3534        | 0.0051        | 0.0051        |
| Manitoba       | 0.0027 | 0.3475        | 0.0027        | 0.0027        |
| New Brunswick  | -0.2719 | -0.2720       | -0.2719       | -0.2719       |
| Newfoundland & Labrador | 0.0873 | 0.0873        | 0.0873        | 0.0873        |
| Nova Scotia    | -0.3400 | -0.3399       | -0.3400       | -0.3400       |
| Ontario        | -0.0991 | -0.0991       | -0.0991       | -0.0991       |
| Prince Edward Island | -0.2458 | -0.2458      | -0.2458       | -0.2458       |
| Quebec         | 0.0286 | 0.0286        | 0.0286        | 0.0286        |
| Saskatchewan   | -0.1627 | -0.1626       | -0.1627       | -0.1627       |
| (Intercepts)   |       |               |               |               |
| Strongly Agree | -4.0870 | -4.0873       | -4.0870       | -4.0870       |
| Agree | -2.0119 | -2.0122       | -2.0119       | -2.0119       |
| Disagree | 0.9929 | 0.9926        | 0.9929        | 0.9929        |

Note that the four response categories are for the question: "People would be afraid to walk alone after dark in this area." The coefficient for the variable "SEX_ASK_TRM" is positive, which suggest that male usually feel safer to walk alone after dark in the living area compared to female. The negative coefficients of "Age_Gpr3: Age65-74" and "Age_Gpr4: Age75+" suggest that older people would feel unsafe to walk alone in the dark. The results are in line with common sense.

Adjusted odds ratios, relative risks and risk ratios

Odds ratios, relative risks and risk ratios can be adjusted to specific factors. Suppose we fit a logistic regression with the indicator variable of the target as the response and the exposure indicator and
confounding variables as dependent variables,
\[
\log(\Pr(\text{Target} = 1 | \text{exposure})) = \beta_0 + \beta_1 \text{exposure} + \sum_i \beta_i \text{confounding}_i
\]

Adjusted odds ratio:
\[
\frac{\Pr(\text{Target} = 1 | \text{exposure} = 1)}{\Pr(\text{Target} = 1 | \text{exposure} = 0)} / \frac{\Pr(\text{Target} = 0 | \text{exposure} = 1)}{\Pr(\text{Target} = 0 | \text{exposure} = 0)} = \exp(\beta)
\]

As suggested by Wacholder (1986), we fit a binomial regression with logarithmic, and identity link functions for the adjusted relative risks, and risk differences, respectively. In the binomial regression with logarithmic link function, we can obtain the adjusted relative risks as
\[
\log(\Pr(\text{Target} = 1 | \text{exposure})) = \beta_0 + \beta_1 \text{exposure} + \sum_i \beta_i \text{confounding}_i
\]

Adjusted relative risk:
\[
\frac{\Pr(\text{Target} = 1 | \text{exposure} = 1)}{\Pr(\text{Target} = 1 | \text{exposure} = 0)} = \exp(\beta).
\]

In the binomial regression with identity link function, we can obtain the adjusted risk differences as
\[
\Pr(\text{Target} = 1 | \text{exposure}) = \beta_0 + \beta_1 \text{exposure} + \sum_i \beta_i \text{confounding}_i
\]

Adjusted risk difference:
\[
\Pr(\text{Target} = 1 | \text{exposure} = 1) - \Pr(\text{Target} = 1 | \text{exposure} = 0) = \beta.
\]

R:

```r
R:
```

SAS:

```sas
/*Adjusted risk ratio without considering the survey design*/
PROC GENMOD data=CLSAData DESCENDING ;
CLASS ORH_EXP_DRM_MCQ SEX_ASK_TRM Age_Grp Education WGHTS_PROV_TRM1 /param=ref;
MODEL ORH_EXP_DRM_MCQ = SEX_ASK_TRM Age_Grp Education WGHTS_PROV_TRM1 /dist=bin link=log ;
WEIGHT WGHTS_ANALYTIC_TRM ;
ODS output ParameterEstimates=Est ;
RUN ;
```

```r
```
RUN;
PROC PRINT data= AdjRR;format _numeric_ 10.8; run;

/**Adjusted risk difference without considering the survey design*/
PROC GENMOD data=CLSAData DESCENDING ;
CLASS ORH_EXP_DRM_MCQ SEX_ASK_TRM Age_Grp Education WGHTS_PROV_TRM / param=ref;
MODEL ORH_EXP_DRM_MCQ = SEX_ASK_TRM Age_Grp Education WGHTS_PROV_TRM /dist=bin link=identity ;
WEIGHT WGHTS_ANALYTIC_TRM;
ODS output ParameterEstimates=AdjRD ;
RUN;
PROC PRINT data= AdjRD(where= (Parameter = "SEX_ASK_TRM"));
format _numeric_ 10.8; RUN;

SPSS:  There is no formal procedure for obtaining adjusted odds ratios, relative risks and risk differences in SPSS.

Stata:
svyset entity_id, strata(StraVar) weight(WGHTS_ANALYTIC_TRM) vce(linearized)
singleunit(certainty)
*adjusted odds ratio
svy linearized: glm ORH_EXP_DRM_MCQ SEX_ASK_TRM i.Age_Grp i.Education i.WGHTS_PROV_TRM ,
   fam(binomial) link(logit) eform
*adjusted relative risk
svy linearized: glm ORH_EXP_DRM_MCQ SEX_ASK_TRM i.Age_Grp i.Education i.WGHTS_PROV_TRM ,
   fam(binomial) link(log) difficult iterate(30000) eform
*adjusted risk difference
svy linearized: glm ORH_EXP_DRM_MCQ SEX_ASK_TRM i.Age_Grp i.Education i.WGHTS_PROV_TRM ,
   fam(binomial) link(identity) difficult iterate(30000)

Results comparison:

|                      | R        | SAS      | Stata    |
|----------------------|----------|----------|----------|
| Adjusted odds ratio  | 0.5901   | 0.5901   | 0.5901   |
| 95% Lower confidence limit | 0.3945   | 0.3927   | 0.3942   |
| 95% Upper confidence limit | 0.8828   | 0.8867   | 0.8834   |
| Adjusted relative risk | 0.6848   | 0.6848   | 0.6848   |
| 95% Lower confidence limit | 0.5039   | 0.5348   | 0.5024   |
| 95% Upper confidence limit | 0.9306   | 0.8768   | 0.9333   |
| Adjusted risk difference | -0.0892  | -0.0883  | -0.0905  |
| 95% Lower confidence limit | -0.1473  | -0.1429  | -0.1556  |
| 95% Upper confidence limit | -0.0311  | -0.0336  | -0.0254  |

We can see the all the packages give the same adjusted odds ratio, relative risk and risk difference. For the latter two cases, the R program and Stata give similar confidence limits as they consider the survey designs in the variance estimation. In contrast, SAS gives significant narrower limits as it ignores the survey design without the SUDAAN package. The adjusted risk differences shown vary among the statistical packages as the convergence is not achieved. The differences are due to assorted stopping criteria implemented in those program.

7. Domain Estimation

If we are interested in a particular group of units in the population, we may consider estimation of subpopulation (domain) means. Domains are a concept at the estimation stage, which are often different from strata which are subpopulations defined at the survey design stage. For instance, we might be interested in people who have a university degree and those who do not have one. Treating the subset of the original survey dataset with units belonging to the domain of interest as if it is a stand-alone survey sample from the domain would yield incorrect standard errors. The following codes describe the correct way to perform domain analyses.
Estimation of domain proportions

If we are interested in understanding how people respond to the question, “People would be afraid to walk alone after dark in this area” (ENV_AFRDWLK_MCQ) among the group of people with or without a university degree, we may use the following codes.

R:

svymean(~ENV_AFRDWLK_MCQ, design=subset(CLSA.design,ED_HIGH_TRM1=="Non_university") )
svymean(~ENV_AFRDWLK_MCQ, design=subset(CLSA.design,ED_HIGH_TRM1=="University") )

SAS:

PROC SURVEYMEANS data= CLSAData mean;
VAR ENV_AFRDWLK_MCQ1;
DOMAIN ED_HIGH_TRM1;
STRATA GEOSTRAT_TRM;
WEIGHT WGHTS_INFLATION_TRM;
RUN;

SPSS:

Analyze → Complex Samples → Frequencies... → Select the file "CLSADesign.csaplan" in the Plan panel → select ENV_AFRDWLK_MCQ to the Frequency Table panel → select ED_HIGH_TRM1 to the “Subpopulations:” panel → click “Statistics...” → select “Table percent” and “Standard error” → click “Continue” → click “OK”.

Stata:

*We first change the survey design to that with inflation survey weight
svyset entity_id, strata(StraVar) weight(WGHTS_INFLATION_TRM) vce(linearized) singleunit(uncertainty)
* For people who never attained any university
svy linearized, subpop(if ED_HIGH_TRM1==0) : tabulate ENV_AFRDWLK_MCQ1 , cell se ci stubwidth(20) format(%10.0g)
* For people who have attained an university
svy linearized, subpop(ED_HIGH_TRM1) : tabulate ENV_AFRDWLK_MCQ1 , cell se ci stubwidth(20) format (%10.0g)

Results comparison:

| ENV_AFRDWLK_MCQ     | R            | SAS          | SPSS         | Stata        |
|---------------------|--------------|--------------|--------------|--------------|
| Group: Non university |              |              |              |              |
| Strongly Agree      | 0.0204 0.0077| 0.0204 0.0077| 0.0204 0.0077| 0.0204 0.0077|
| Agree               | 0.1006 0.0161| 0.1006 0.0161| 0.1006 0.0161| 0.1006 0.0161|
| Disagree            | 0.5751 0.0288| 0.5751 0.0288| 0.5751 0.0288| 0.5751 0.0288|
| Strongly Disagree   | 0.2316 0.0254| 0.2316 0.0254| 0.2316 0.0254| 0.2316 0.0254|
| Missing             | 0.0723 0.0165| 0.0723 0.0165| 0.0723 0.0165| 0.0723 0.0165|
| Group: University   |              |              |              |              |
| Strongly Agree      | 0.0112 0.0064| 0.0112 0.0064| 0.0112 0.0064| 0.0112 0.0064|
| Agree               | 0.0751 0.0197| 0.0751 0.0197| 0.0751 0.0197| 0.0751 0.0197|
| Disagree            | 0.5683 0.0351| 0.5683 0.0351| 0.5683 0.0351| 0.5683 0.0351|
| Strongly Disagree   | 0.3112 0.0331| 0.3112 0.0331| 0.3112 0.0331| 0.3112 0.0331|
| Missing             | 0.0342 0.0121| 0.0342 0.0121| 0.0342 0.0121| 0.0342 0.0121|

Estimation of domain quantiles

If we may want to estimate the population quantiles and medians of the self-reported body weight and body height among people with or without a university degree, we may consider the following codes.
# For people who did not attend an university
Quant.NUni<- svyquantile( ~ HWT_DHT_M_TRM+HWT_WGHT_KG_TRM , quantile=c(0.025,0.5,0.975),
alpha=0.05 ,interval.type="Wald", design= subset(CLSA.design,ED_HIGH_TRM1=="Non_university"),
ties=c("rounded"), ci= TRUE, se=TRUE )
Quant.NUni; SE(Quant.NUni);

# For people who attended an university
Quant.Uni<-svyquantile( ~ HWT_DHT_M_TRM+HWT_WGHT_KG_TRM , quantile=c(0.025,0.5,0.975),
alpha=0.05 , interval.type="Wald", design= subset(CLSA.design,ED_HIGH_TRM1=="University"),
ties=c("rounded"), ci= TRUE, se=TRUE )
Quant.Uni; SE(Quant.Uni);

In SAS, SPSS and Stata packages, there is no formal procedure available to produce quantile estimates for domain analysis.

**R program Output:**

| Quantiles | HWT_DHT_M_TRM Non_university | HWT_DHT_M_TRM University | HWT_WGHT_KG_TRM Non_university | HWT_WGHT_KG_TRM University |
|-----------|-------------------------------|--------------------------|--------------------------------|---------------------------|
| 0.025     | 1.5109                        | 1.5137                   | 48.9258                        | 51.3353                   |
| 0.05      | 1.5311                        | 1.5311                   | 51.7980                        | 53.9833                   |
| 0.1       | 1.5537                        | 1.5571                   | 55.4990                        | 57.4062                   |
| 0.5       | 1.6579                        | 1.6711                   | 76.7963                        | 73.4840                   |
| 0.9       | 1.7714                        | 1.8003                   | 101.5681                       | 94.5099                   |
| 0.95      | 1.8024                        | 1.8276                   | 109.9035                       | 99.9627                   |
| 0.975     | 1.8277                        | 1.8682                   | 122.8340                       | 108.1732                  |

| SE        | HWT_DHT_M_TRM Non_university | HWT_DHT_M_TRM University | HWT_WGHT_KG_TRM Non_university | HWT_WGHT_KG_TRM University |
|-----------|-------------------------------|--------------------------|--------------------------------|---------------------------|
| 0.025     | 0.0073                        | 0.0013                   | 1.0451                         | 1.9207                    |
| 0.05      | 0.0051                        | 0.00102                  | 0.8544                         | 0.6790                    |
| 0.1       | 0.0052                        | 0.00064                  | 0.9990                         | 0.9227                    |
| 0.5       | 0.0072                        | 0.00090                  | 1.2966                         | 1.2862                    |
| 0.9       | 0.0108                        | 0.0120                   | 3.1358                         | 2.3605                    |
| 0.95      | 0.0141                        | 0.0224                   | 3.9499                         | 3.5970                    |
| 0.975     | 0.0300                        | 0.0315                   | 7.2118                         | 5.2620                    |

**Linear regression in domain analysis**

If we want to investigate the relationship of self-reported height and weight within the subpopulation which are interviewed in English, we may apply the following codes.

**R:**

R: LinearReg_EN<-svyglm( HWT_DHT_M_TRM~ HWT_WGHT_KG_TRM+SEX_ASK_TRM + Age_Grp+Education +
WGHTS_PROV_TRM1, family="gaussian", design=subset(CLSA.design.anly, startlanguage="en" ) )
summary(LinearReg_EN)

**SAS:**

SAS:

PROC SURVEYREG data=CLSAData ;
CLASS SEX_ASK_TRM Age_Grp Education WGHTS_PROV_TRM1;
MODEL HWT_DHT_M_TRM = HWT_WGHT_KG_TRM SEX_ASK_TRM Age_Grp Education WGHTS_PROV_TRM1 / solution ;
WEIGHT WGHTS_ANALYTIC_TRM;
STRATA GEOSTRAT_TRM ;
DOMAIN startlanguage;
ods output ParameterEstimates=Est;
RUN;

PROC PRINT data= EST;
where startlanguage =="en";
format _numeric_ 15.9; run;
SPSS:
Analyze → Complex Samples → General Linear Model... → Select the file "CLSADesignAny.csaplan" in the Plan panel → select [Target Variables] to the "Dependent Variable", "Factor" and "Covariate" panels → select "startlanguage" to the "Subpopulations" panel and enter the target category → click "Statistics..." → select "Estimate" and "Standard error" → click "Continue" → click "OK".

Stata:
svyset entity_id, strata(StraVar) weight(WGHTS_ANALYTIC_TRM) vce(linearized)
svy linearized, subpop(if startlanguage = "en"):
regress HWT_DHT_M_TRM HWT_WGHT_KG_TRM SEX_ASK_TRM i.Age_Grp i.Education i.WGHTS_PROV_TRM
estimates table, b(%10.0g) se(%10.0g)

Results comparison:

| Population Est. | R | SAS | SPSS | Stata |
|-----------------|---|-----|------|-------|
| (Intercept)     | 1.62E+0 1.832E-2 | 1.62E+0 1.850E-2 | 1.62E+0 1.832E-2 | 1.62E+0 1.832E-2 |
| HWT_WGHT_KG_TRM | -6.692E-6 2.552E-6 | -6.692E-6 2.578E-6 | -6.692E-6 2.552E-6 | -6.692E-6 2.552E-6 |
| SEX_ASK_TRM     | 1.284E-1 6.105E-3 | 1.284E-1 6.166E-3 | 1.284E-1 6.105E-3 | 1.284E-1 6.105E-3 |
| Age Groups      |                           |                           |                           |
| Age_Grp1: Age 45-54 | | | | |
| Age_Grp2: Age 55-64 | 1.586E-2 9.971E-3 | 1.586E-2 1.007E-2 | 1.586E-2 9.971E-3 | 1.586E-2 9.971E-3 |
| Age_Grp3: Age 65-74 | 8.436E-3 1.039E-2 | 8.436E-3 1.049E-2 | 8.436E-3 1.039E-2 | 8.436E-3 1.039E-2 |
| Age_Grp4: Age 75+ | -8.594E-3 1.311E-2 | -8.594E-3 1.324E-2 | -8.594E-3 1.311E-2 | -8.594E-3 1.311E-2 |
| Education Levels |                           |                           |                           |
| Medium Education | -8.157E-3 1.402E-2 | -8.157E-3 1.416E-2 | -8.157E-3 1.402E-2 | -8.157E-3 1.402E-2 |
| Higher Education lower | -4.174E-3 1.393E-2 | -4.174E-3 1.407E-2 | -4.174E-3 1.393E-2 | -4.174E-3 1.393E-2 |
| Higher Education upper | 1.050E-2 1.381E-2 | 1.050E-2 1.395E-2 | 1.050E-2 1.381E-2 | 1.050E-2 1.381E-2 |
| Provinces       |                           |                           |                           |
| British Columbia | 1.386E-2 1.081E-2 | 1.386E-2 1.092E-2 | 1.386E-2 1.081E-2 | 1.386E-2 1.081E-2 |
| Manitoba        | 7.181E-3 1.179E-2 | 7.181E-3 1.191E-2 | 7.181E-3 1.179E-2 | 7.181E-3 1.179E-2 |
| New Brunswick   | 4.231E-3 1.299E-2 | 4.231E-3 1.312E-2 | 4.231E-3 1.299E-2 | 4.231E-3 1.299E-2 |
| Newfoundland & Labrador | -7.063E-4 1.161E-2 | -7.063E-4 1.172E-2 | -7.063E-4 1.161E-2 | -7.063E-4 1.161E-2 |
| Nova Scotia     | 5.168E-3 1.215E-2 | 5.168E-3 1.227E-2 | 5.168E-3 1.215E-2 | 5.168E-3 1.215E-2 |
| Ontario         | -5.462E-5 1.111E-2 | -5.462E-5 1.122E-2 | -5.462E-5 1.111E-2 | -5.462E-5 1.111E-2 |
| Prince Edward Island | -7.639E-3 1.234E-2 | -7.639E-3 1.247E-2 | -7.639E-3 1.234E-2 | -7.639E-3 1.234E-2 |
| Quebec          | -2.335E-3 1.071E-2 | -2.335E-3 1.082E-2 | -2.335E-3 1.071E-2 | -2.335E-3 1.071E-2 |
| Saskatchewan    | -1.479E-2 1.294E-2 | -1.479E-2 1.307E-2 | -1.479E-2 1.294E-2 | -1.479E-2 1.294E-2 |

Logistic regression in domain analysis

If we want to investigate the experiencing dry mouth indicated by the variable "ORH_EXP_DRM_MCQ" for the group of people who responses in English, we may apply the following codes.

R:

LogisticReg3_EN<-svyglm( ORH_EXP_DRM_MCQ ~ SEX_ASK_TRM+ Age_Grp+Education + WGHTS_PROV_TRM1, family=quasibinomial, design=subset(CLSA.design.anly, startlanguage="en" ))
summary(LogisticReg3_EN)

SAS:

PROC SURVEYLOGISTIC data=CLSAData;
class ORH_EXP_DRM_MCQ(ref=first) SEX_ASK_TRM Age_Grp Education WGHTS_PROV_TRM1 /param=ref;
model ORH_EXP_DRM_MCQ = SEX_ASK_TRM Age_Grp Education WGHTS_PROV_TRM1 /clodds;
strata GEOSTRAT_TRM;
weight WGHTS_ANALYTIC_TRM;
DOMAIN startlanguage;
ods output ParameterEstimates=Est;
RUN;

PROC PRINT data= EST;
where startlanguage ="en";
format _numeric_ 15.9; run;

SPSS:
Analyze → Complex Samples → Logistic Regression... → Select the file "CLSADesignAny1.casplan" in the Plan panel →select [Target Variables] to the "Dependent Variable", "Factor" and "Covariate" panels → Select startlanguage to "Subpopulation" and enter the target category → Click "Reference Category" and select "Lowest value" → Click "Statistics..." → select "Estimate" and "Standard error" → Click "Continue" → Click "OK".

Stata:
svyset entity_id, strata(StraVar) weight(WGHTS_ANALYTIC_TRM) vce(linearized) singleunit(certainty)
svy linearized, subpop(if startlanguage=="en"): logit ORH_EXP_DRM_MCQ SEX_ASK_TRM 
i.Age_Grp i.Education i.WGHTS_PROV_TRM

Results comparison:

| Population Est. | R     | SAS | SPSS     | Stata |
|-----------------|-------|-----|----------|-------|
| (Intercept)     | -1.1999 | 0.6269 | -1.1999 | 0.6268 |
| SEX_ASK_TRM     | -0.4935 | 0.2430 | -0.4935 | 0.2429 |
| Age Groups      |       |     |          |       |
| (rel. to Age_Gpr1: Age 45-54) |       |     |          |       |
| Age_Gpr2:Age 55-64 | 0.5201 | 0.3854 | 0.5201 | 0.3854 |
| Age_Gpr3:Age 65-74 | 0.6968 | 0.3931 | 0.6968 | 0.3931 |
| Age_Gpr4:Age 75+ | 0.5663 | 0.5104 | 0.5663 | 0.5104 |
| Education Levels |       |     |          |       |
| (rel. to Lower Education) |       |     |          |       |
| Higher Education lower | 0.0865 | 0.4430 | 0.0865 | 0.4430 |
| Higher Education upper | 0.0382 | 0.4411 | 0.0382 | 0.4411 |
| Provinces       |       |     |          |       |
| (rel. to Alberta) |       |     |          |       |
| British Columbia | -0.9167 | 0.4557 | -0.9167 | 0.4557 |
| Manitoba       | -0.2713 | 0.4404 | -0.2713 | 0.4404 |
| New Brunswick  | 0.0530  | 0.4624 | 0.0530  | 0.4624 |
| Newfoundland & Labrador | -0.4328 | 0.4701 | -0.4328 | 0.4701 |
| Nova Scotia    | 0.3214  | 0.4465 | 0.3214  | 0.4465 |
| Ontario        | -0.2059 | 0.4234 | -0.2059 | 0.4234 |
| Prince Edward Island | -0.3867 | 0.4742 | -0.3867 | 0.4742 |
| Quebec         | 0.0334  | 1.2551 | 0.0334  | 1.2551 |

Multinomial logistic regression in domain analysis

Suppose we are interested in the current marital statuses (single, married and others) of the subpopulation which uses English to answer the questionnaire.

R: There is no official support for multinomial regression from the R survey package.

SAS:
PROC SURVEYLOGISTIC data=CLSAExample ;
class WEA_MRTL_CURRENT_MCQ2 SEX_ASK_TRM Age_Grp Education WGHTS_PROV_TRM /param=ref ;
model WEA_MRTL_CURRENT_MCQ2 = SEX_ASK_TRM Age_Grp Education WGHTS_PROV_TRM /clodds link=glogit ;
strata GEOSTRAT_TRM;
weight WGHTS_ANALYTIC_TRM;
DOMAIN startlanguage;
ods output ParameterEstimates=Est;
RUN;

Proc sort data= EST Out= MyParmEst ;
by Response;
where startlanguage = "en";
run;

Proc print data= MyParmEst; run;

SPSS:

Analyze → Complex Samples → Logistic Regression... → Select the file "CLSADesignAnyl.csaplan" in the Plan panel → click "Continue" → select the corresponding variables to the "Dependent Variable", "Factor" and "Covariate" panels → click "Reference Category" and select "Lowest value" → select "startlanguage" to the "Subpopulations" panel and enter the target category → click "Statistics..." → select "Estimate" and "Standard error" → click "Continue" → click "OK".

Stata:

.svy linearized, subpop(if startlanguage=="en") : mlogit  MRTL_CURRENT1  SEX_ASK_TRM  
   i.Age_Grp i.Education i.WGHTS_PROV_TRM, baseoutcome(1)

Results comparison
### Response: Marital status

|       | SAS               | SPSS              | Stata             |
|-------|-------------------|-------------------|-------------------|
|       | Coeff.  | SE    | Coeff.  | SE    | Coeff.  | SE    |
| 2:Married (Intercept) | 1.4474  | 0.8645 | 1.4474  | 0.8472 | 1.4474  | 0.8473 |
|       | SEX_ASK_TRM |       |       |       |       |       |
| Age Groups (rel. to Age_Gpr: Age 45-54) |       |       |       |       |       |       |
| Age_Grp2:Age 55-64 | 0.1035  | 0.4614 | 0.1035  | 0.4522 | 0.1035  | 0.4522 |
| Age_Grp3:Age 65-74 | 0.2171  | 0.5082 | 0.2171  | 0.4981 | 0.2171  | 0.4981 |
| Age_Grp4:Age 75+ | 0.0641  | 0.7510 | 0.0641  | 0.7361 | 0.0642  | 0.7360 |
| Education Levels (rel. to Lower Education) |       |       |       |       |       |       |
| Medium Education | 0.7869  | 0.6700 | 0.7869  | 0.6566 | 0.7868  | 0.6566 |
| Higher Education lower | 0.6634  | 0.6757 | 0.6634  | 0.6622 | 0.6632  | 0.6622 |
| Higher Education upper | 0.6766  | 0.6598 | 0.6766  | 0.6466 | 0.6765  | 0.6466 |
| Provinces (rel. to Alberta) |       |       |       |       |       |       |
| British Columbia | 0.1227  | 0.6426 | -0.1227 | 0.6298 | -0.1227 | 0.6298 |
| Manitoba | -0.5767  | 0.5746 | -0.5767 | 0.5632 | -0.5767 | 0.5632 |
| New Brunswick | 1.1966  | 0.9283 | 1.1966  | 0.9098 | 1.1964  | 0.9096 |
| Newfoundland & Labrador | 0.0134  | 0.7622 | 0.0134  | 0.7470 | 0.0134  | 0.7470 |
| Nova Scotia | 0.3181  | 0.7298 | 0.3181  | 0.7152 | 0.3181  | 0.7152 |
| Ontario | -0.4385  | 0.5925 | -0.4386 | 0.5807 | -0.4385 | 0.5807 |
| Prince Edward Island | -1.2155 | 0.6200 | -1.2156 | 0.6076 | -1.2155 | 0.6076 |
| Quebec | 10.8952  | 1.0901 | 19.8953 | 44.4727 | 11.0231 | 1.0684 |
| Saskatchewan | 1.6480  | 1.1639 | 1.6480  | 1.1407 | 1.6479  | 1.1405 |
| 3:Others (Intercept) | -0.3943  | 1.0915 | -0.3943 | 1.0697 | -0.3941 | 1.0700 |
| SEX_ASK_TRM | -0.9348  | 0.4082 | -0.9348 | 0.4000 | -0.9348 | 0.4000 |
| Age Groups (rel. to Age_Gpr: Age 45-54) |       |       |       |       |       |       |
| Age_Grp2:Age 55-64 | 0.7266  | 0.6366 | 0.7266  | 0.6239 | 0.7266  | 0.6239 |
| Age_Grp3:Age 65-74 | 1.2753  | 0.6375 | 1.2753  | 0.6542 | 1.2753  | 0.6542 |
| Age_Grp4:Age 75+ | 2.4720  | 0.8747 | 2.4720  | 0.8573 | 2.4717  | 0.8573 |
| Education Levels (rel. to Lower Education) |       |       |       |       |       |       |
| Medium Education | 1.3776  | 0.7555 | 1.3776  | 0.7405 | 1.3774  | 0.7405 |
| Higher Education lower | 1.0669  | 0.7652 | 1.0669  | 0.7500 | 1.0668  | 0.7500 |
| Higher Education upper | 0.7486  | 0.7482 | 0.7486  | 0.7333 | 0.7485  | 0.7333 |
| Provinces (rel. to Alberta) |       |       |       |       |       |       |
| British Columbia | -0.5309  | 0.7182 | -0.5309 | 0.7039 | -0.5309 | 0.7039 |
| Manitoba | -0.4322  | 0.6666 | -0.4322 | 0.6533 | -0.4322 | 0.6533 |
| New Brunswick | 0.8279  | 0.9989 | 0.8279  | 0.9790 | 0.8276  | 0.9788 |
| Newfoundland & Labrador | -0.9295 | 0.8564 | -0.9295 | 0.8394 | -0.9295 | 0.8394 |
| Nova Scotia | 0.1844  | 0.8124 | 0.1844  | 0.7961 | 0.1845  | 0.7961 |
| Ontario | -0.9148  | 0.6883 | -0.9148 | 0.6745 | -0.9148 | 0.6746 |
| Prince Edward Island | -1.3522 | 0.7260 | -1.3522 | 0.7116 | -1.3522 | 0.7116 |
| Quebec | 11.7396  | 1.1539 | 20.7397 | 44.4759 | 11.8674 | 1.1309 |
| Saskatchewan | 1.1034  | 1.2184 | 1.1034  | 1.1941 | 1.1032  | 1.1940 |

### Ordinal logistic regression in domain analysis

Suppose we are interested in the variable `ENV_AFRDLWLK_MCQ2` for the group of people who answer the questionnaire.

**R:**

```r
summary( svyolr(formula = ENV_AFRDLWLK_MCQ2 ~ SEX_ASK_TRM + Age_Grp + Education + WGHTS_PROV_TRM1, design = subset(CLSA.design.anly, startlanguage == "en"), na.action = na.omit, method = c("logistic")) )
```

**SAS:**

```sas
PROC SURVEYLOGISTIC data=CLSAData;
class ENV_AFRDLWLK_MCQ2 SEX_ASK_TRM Age_Grp Education WGHTS_PROV_TRM1 /param=ref;
model ENV_AFRDLWLK_MCQ2 = SEX_ASK_TRM Age_Grp Education WGHTS_PROV_TRM1 /clodds;
strata GEOSTRAT_TRM;
weight WGHTS_ANALYTIC_TRM;
DOMAIN startlanguage;
```
ods output ParameterEstimates=Est;
RUN;

Proc print data= EST;
where startlanguage = "en";
run;

SPSS:
Analyze → Complex Samples → Ordinal Regression...
→ Select the file "CLSADesignAny1.csaplan" in the Plan panel → click "Continue" → select the corresponding variables to the "Dependent Variable", "Factor" and "Covariate" panels → click "Response Probabilities" and select "Accumulate from lowest value of dependent variable to highest value" → select "startlanguage" to the "Subpopulations" panel and enter the target category → click "Statistics..." → select "Estimate" and "Standard error" → click "Continue" → click "OK".

Stata:
svy linearized, subpop(if startlanguage=="en"): ologit ENV_AFRDWLK_MCQ2 SEX_ASK_TRM i.Age_Grp i.Education i.WGHTS_PROV_TRM

Results comparison:

|                        | R      | SAS     | SPSS    | Stata   |
|------------------------|--------|---------|---------|---------|
| Population Est.        | SEX_ASK_TRMM |        |         |         |
|                        | 0.1143 | 0.1856  | 0.1143  | 0.1857  |
| Age Groups             |        |         |         |         |
| (rel. to Age_Grp1; Age 45-54) |        |         |         |         |
| Age_Grp2; Age 55-64    | -0.1966| -0.2905 | -0.1966| -0.2906 |
| Age_Grp3; Age 65-74    | -0.2809| 0.3042  | -0.2809| 0.3042  |
| Age_Grp4; Age 75+      | -1.3462| 0.4110  | -1.3462| 0.4111  |
| Education Levels       |        |         |         |         |
| (rel. to Lower Education) |        |         |         |         |
| Medium Education       | -0.4414| 0.5166  | -0.4414| 0.5164  |
| Higher Education lower | -0.4246| 0.5075  | -0.4246| 0.5075  |
| Higher Education upper | 0.2872 | 0.4957  | 0.2872 | 0.4955  |
| Provinces              |        |         |         |         |
| (rel. to Alberta)      |        |         |         |         |
| British Columbia       | 0.0473 | 0.3470  | 0.0473 | 0.3472  |
| Manitoba               | -0.0188| 0.3430  | -0.0188| 0.3431  |
| New Brunswick          | -0.3852| 0.3835  | -0.3852| 0.3856  |
| Newfoundland & Labrador| 0.0984 | 0.3654  | 0.0984 | 0.3657  |
| Nova Scotia            | -0.2964| 0.4086  | -0.2964| 0.4090  |
| Ontario                | 0.0354 | 0.3114  | 0.0354 | 0.3115  |
| Prince Edward Island   | -0.2438| 0.3729  | -0.2438| 0.3730  |
| Quebec                 | 1.6611 | 1.3156  | 1.6611 | 1.3156  |
| Saskatchewan           | -0.1442| 0.3590  | -0.1442| 0.3591  |
| (Intercepts)           |        |         |         |         |
| Strongly Agree | Agree | Disagree | Strongly Disagree | | |
|                      | 4.6354 | 0.6558  | 4.6359 | 0.6316  | 4.6354 | 0.6556  | 4.6354 | 0.6557  |
|                      | 2.3937 | 0.5952  | 2.3942 | 0.5627  | 2.3937 | 0.5950  | 2.3937 | 0.5951  |
|                      | 0.5987 | 0.5916  | 0.5987 | 0.5997  | 0.5987 | 0.5916  | 0.5987 | 0.5916  |

Adjusted odds ratio, relative risks and risk ratios in domain analysis

Suppose we want to study the relationship of experiencing dry mouth in the past 12 months (ORH_EXP_DRM_MCQ) with sex (SEX_ASK_TRM) adjusted by the province variable (WGHTS_PROV_TRM), age groups and the individual education for the people who complete the questionnaire with English, we can obtain the odds ratio, relative risk and risk ratio by the following codes:

R: As the number of dependent variable is large, we may need to specify the initial values in the "start" option.

## Adjusted odds ratio
Adj.OR <- svyglm( ORH_EXP_DRM_MCQ ~ SEX_ASK_TRM + Age_Grp + Education + WGHTS_PROV_TRM1 ,
family=quasibinomial(link="log"), design=subset(CLSA.design.anly, startlanguage == "en"))

exp(coef(Adj.OR)["SEX_ASK_TRM"]); exp(confint(Adj.OR)["SEX_ASK_TRM",])

## Adjusted risk ratio

Adj.RR <- svyglm( ORH_EXP_DRM_MCQ ~ SEX_ASK_TRM + Age_Grp + Education + WGHTS_PROV_TRM1, family=quasibinomial(link="log"), design=subset(CLSA.design.anly, startlanguage == "en"), start= c(-0.49, -0.45, 0.08, 0.42, 0.19, -0.59, -0.53, -0.61, -0.90, -0.44, -0.33, -0.47, -0.11, -0.41, -0.63, -0.59, -0.66))

exp(coef(Adj.RR)["SEX_ASK_TRM"]); exp(confint(Adj.RR)["SEX_ASK_TRM",])

## Adjusted risk difference

Adj.RD <- svyglm( ORH_EXP_DRM_MCQ ~ SEX_ASK_TRM + Age_Grp + Education + WGHTS_PROV_TRM1, family=quasibinomial(link="identity"), design=subset(CLSA.design.anly, startlanguage == "en"), start= c(0.32, -0.09, 0.08, 0.15, 0.17, -0.06, -0.05, -0.06, -0.16, -0.05, -0.01, 0.07, -0.06, -0.09, -0.10, -0.15))

coeff(Adj.RD)["SEX_ASK_TRM"] ; confint(Adj.RD)["SEX_ASK_TRM",]

SAS: There is no formal procedure for the adjusted relative risk and risk ratios. We would compare the results from PROC GENMOD and the appropriate procedures from other statistic packages. The correct approach can be archived with the SUDAAN package which we would not discuss here. Interested readers may refer to Bieler et al. (2010).

PROC SURVEYLOGISTIC data=CLSAData;
CLASS ORH_EXP_DRM_MCQ SEX_ASK_TRM Age_Grp Education WGHTS_PROV_TRM1/param=ref;
MODEL ORH_EXP_DRM_MCQ (event='1')= SEX_ASK_TRM Age_Grp Education WGHTS_PROV_TRM1 /clodds;
STRATA GEOSTRAT_TRM;
WEIGHT WGHTS_ANALYTIC_TRM;
DOMAIN startlanguage;
OOS output CLOddsWald=CLOddsWald;
RUN;
PROC PRINT data=CLOddsWald;
format _numeric_ 10.8;
where startlanguage eq "en";
title "Odds Ratio Estimates";
RUN;

/*Adjusted risk ratio without considering the survey design*/
PROC GENMOD data=CLSAData DESCENDING;
CLASS ORH_EXP_DRM_MCQ SEX_ASK_TRM Age_Grp Education WGHTS_PROV_TRM1/param=ref;
MODEL ORH_EXP_DRM_MCQ (event='1')= SEX_ASK_TRM Age_Grp Education WGHTS_PROV_TRM1 /dist=bin link=log;
WEIGHT WGHTS_ANALYTIC_TRM;
where startlanguage eq "en";
OOS output ParameterEstimates=Est;
RUN;
Data AdjRR;
SET Est(where=(Parameter ="SEX_ASK_TRM"));
AdjRR= exp(Estimate);
AdjRRLL = exp( LowerWALDCL);
AdjRRUL = exp( UpperWALDCL);
RUN;
PROC PRINT data= AdjRR;format _numeric_ 10.8; run;

/*Adjusted risk difference without considering the survey design*/
PROC GENMOD data=CLSAData DESCENDING;
CLASS ORH_EXP_DRM_MCQ SEX_ASK_TRM Age_Grp Education WGHTS_PROV_TRM1/param=ref;
MODEL ORH_EXP_DRM_MCQ (event='1')= SEX_ASK_TRM Age_Grp Education WGHTS_PROV_TRM1 /dist=bin link=identity;
where startlanguage eq "en";
OOS output ParameterEstimates=AdjRD;
RUN;
PROC PRINT data= AdjRD(where=(Parameter ="SEX_ASK_TRM"));
format _numeric_ 10.8; RUN;
SPSS: There is no formal procedure for obtaining adjusted odds ratios, relative risks and risk differences in SPSS.

Stata:

```stata
svyset entity_id, strata(StraVar) weight(WGHTS_ANALYTIC_TRM) vce(linearized)
singleunit(certainty)

# adjusted odds ratio
svy linearized: glm ORH_EXP_DRM_MCQ SEX_ASK_TRM i.Age_Grp i.Education
i.WGHTS_PROV_TRM , fam(binomial) link(logit) eform

# adjusted relative risk
svy linearized: glm ORH_EXP_DRM_MCQ SEX_ASK_TRM i.Age_Grp i.Education
i.WGHTS_PROV_TRM , fam(binomial) link(log) difficult iterate(30000) eform

# adjusted risk difference
svy linearized: glm ORH_EXP_DRM_MCQ SEX_ASK_TRM i.Age_Grp i.Education
i.WGHTS_PROV_TRM , fam(binomial) link(identity) difficult iterate(30000)
```

Results comparison:

|                         | R    | SAS   | Stata |
|-------------------------|------|-------|-------|
| Adjusted odds ratio     | 0.6105 | 0.6105 | 0.6105 |
| 95% Lower confidence limit | 0.3792 | 0.3725 | 0.3790 |
| 95% Upper confidence limit | 0.9829 | 0.9879 | 0.9835 |
| Adjusted relative risk  | 0.7028 | 0.7028 | 0.7028 |
| 95% Lower confidence limit | 0.4908 | 0.5313 | 0.4866 |
| 95% Upper confidence limit | 1.0063 | 0.9296 | 1.0150 |
| Adjusted risk difference | -0.0827 | -0.0794 | -0.0844 |
| 95% Lower confidence limit | -0.1523 | -0.1471 | -0.1635 |
| 95% Upper confidence limit | -0.0132 | -0.0117 | -0.0553 |

Again, we can see the all the packages give the same adjusted odds ratio, relative risk and risk difference. For the latter two cases, the R program and Stata give similar confidence limits as they consider the survey designs in the variance estimation. In contrast, SAS gives noticeably narrower limits as it ignores the survey design without the SUDAAN package. The adjusted risk differences shown vary among the statistical packages as the convergence is not achieved. The differences are due to assorted stopping criteria implemented in those program.

This domain analysis is for the researchers who are just interested in the adjusted odds ratios, relative risks and risk differences of the sub population. If the comparison of the odds ratio between different sub populations is preferred, then we suggest adding the sub-population indicators as part of the covariates in the regression equations to obtain the adjusted odds ratios.

What if we ignore domain analysis

If we do not specify the subpopulation in a survey and treat the subset of the dataset as a separate survey, the resulting standard error would be incorrect. We would compare the difference in SE by the R program. Here, we give an extreme example to emphasize the effect if we do not specify the subpopulation. Suppose we are interested in the ENV_AFRDWLK_MCQ variable and want to compare it between people with BMI below and above 19. There are 22 and 842 respondents with BMI < 19 and those have at least 19, respectively. Here are the codes for such a comparison.

```r
# It is correct to specify the subpopulations
svytotal(~ENV_AFRDWLK_MCQ1, design=subset(CLSA.design,BMI<19) )
svytotal(~ENV_AFRDWLK_MCQ1, design=subset(CLSA.design,BMI>=19))

# It is not appropriate if we divide the dataset and re-declare the survey design
CLSAData.low.BMI <- CLSAData[which(CLSAData$BMI<19), ]
CLSAData.high.BMI <- CLSAData[which(CLSAData$BMI>=19), ]

CLSA.design.low.BMI<- svydesign( ids= ~ entity_id, strata = ~ StraVar,
weights = ~ WHTS_INFLATION_TRM, data= CLSAData.low.BMI, nest =TRUE )

CLSA.design.high.BMI<- svydesign( ids= ~ entity_id, strata = ~ StraVar,
```

weights = ~ WGHTS_INFLATION_TRM, data= CLSADatA.high.BMI, nest = TRUE 

svytotal(~ENV_AFRDWLK_MCQ1, design=CLSA.design.low.BMI)
svytotal(~ENV_AFRDWLK_MCQ1, design=CLSA.design.high.BMI)

Results comparison:

| Subpopulation          | Specified | Not Specified |
|------------------------|-----------|---------------|
|                        | Total SE  | Total SE      |
|                        |           |               |
| Group:BMI < 19         |           |               |
| Strongly Agree         | 644.35    | 644.35        |
| Agree                  | 3296.81   | 1957.95       |
| Disagree               | 5474.52   | 1545.81       |
| Strongly Disagree      | 1022.27   | 1022.27       |
| Missing                | 252.07    | 252.07        |
| Group:BMI ≥ 19         |           |               |
| Strongly Agree         | 7969.5    | 2635.4        |
| Agree                  | 43421.6   | 6251.3        |
| Disagree               | 291481.6  | 12714.4       |
| Strongly Disagree      | 136278    | 10955.7       |
| Missing                | 29058.6   | 5682.1        |

Readers can see that the estimates for the total are the same for both groups, while there are substantial differences in the standard error. If we specify the subpopulation, the standard errors given by the program would be more reasonable and generally slightly higher. It is because the statistical package would treat the sizes of subpopulations to be random in domain analysis, and therefore, there is more uncertainty in the population estimates.

Note: The total of the sub population estimates from the table above is much smaller than the CLSA study population. It is because the dataset used for illustration is only a subset of the CLSA dataset. The actual dataset should give much larger sub population totals.

8. Concluding remarks

This paper has outlined the appropriate steps to import, prepare and analyze datasets from CLSA using R, SAS, SPSS and Stata. From the comparisons presented in the paper, we see that R provides accurate and reliable estimates and standard errors as an attractive statistical package. The data manipulation and analysis codes in R described in the paper can be generalized to other datasets from surveys with a sampling scheme similar to the CLSA.

This paper highlights the comparison of the codes between R and other commercial statistical packages for different statistical procedures. The survey packages in R provides most of the procedures in which health policy researchers are interested. Comparing with other packages, R is easy to use, flexible and open-source. We recommend that health researchers choose R as one of the statistical packages for data analyses.

This paper can also serve as a cookbook for the health policy analysts who can check the corresponding codes for various statistical analyses for different statistical packages. This paper would be part of the groundwork for health-care survey administration organizations to include instructions and sample R codes in their technical documentation.

Version notes

The calculations in this paper were performed with R version 3.6.3, using the R survey package version 3.37. Statistical package comparisons were calculated using SAS version 9.4 with SAS/STAT version 15.1, SPSS Version 25 and Stata/SE version 15.0.
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