

# Estimation of Social Exclusion Indicators from Complex Surveys: The R Package *laeken*

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## Abstract

This package vignette is an up-to-date version of [Alfons and Templ \(2013\)](#), published in the *Journal of Statistical Software*.

Units sampled from finite populations typically come with different inclusion probabilities. Together with additional preprocessing steps of the raw data, this yields unequal sampling weights of the observations. Whenever indicators are estimated from such complex samples, the corresponding sampling weights have to be taken into account. In addition, many indicators suffer from a strong influence of outliers, which are a common problem in real-world data. The R package **laeken** is an object-oriented toolkit for the estimation of indicators from complex survey samples via standard or robust methods. In particular the most widely used social exclusion and poverty indicators are implemented in the package. A general calibrated bootstrap method to estimate the variance of indicators for common survey designs is included as well. Furthermore, the package contains synthetically generated close-to-reality data for the European Union Statistics on Income and Living Conditions and the Structure of Earnings Survey, which are used in the code examples throughout the paper. Even though the paper is focused on showing the functionality of package **laeken**, it also provides a brief mathematical description of the implemented indicator methodology.

*Keywords:* indicators, robust estimation, sample weights, survey methodology, R.

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## 1. Introduction

Estimation of indicators is one of the main tasks in survey statistics. They are usually estimated from complex surveys with many thousands of observations, conducted in a harmonized manner over many countries. Indicators are designed to reflect major developments in society, for example with respect to poverty, social cohesion or gender inequality, in order to quantify and monitor progress towards policy objectives. Moreover, by implementing a monitoring system across countries via a harmonized set of indicators, different policies can be compared based on quantitative information regarding their impact on society. Thus statistical indicators are an important source of information on which policy makers can base their decisions.

Nevertheless, for policy decisions to be effective, the underlying quantitative information from the indicators needs to be reliable. Not only should the variability of the indicators be kept in mind, but also the impact of data collection and preprocessing needs to be considered. Indicators are typically based on complex surveys, in which units are drawn from finite popu-

lations, most often with unequal inclusion probabilities. Hence the observations in the sample represent different numbers of units in the population, giving them unequal sample weights. In addition, those initial weights are often modified by preprocessing steps such as calibration for nonresponse. Therefore, sample weights always need to be taken into account in the estimation of indicators from survey samples, otherwise the estimates may be biased.

The focus of this paper is on socioeconomic indicators on poverty, social cohesion and gender differences. In economic data, extreme outliers are a common problem. Such outliers can have a disproportionately large influence on the estimates of indicators and may completely distort them. If indicators are corrupted by outliers, wrong conclusions could be drawn by policy makers. Robust estimators that give reliable estimates even in the presence of extreme outliers are therefore necessary.

We introduce the add-on package **laeken** (Alfons, Holzer, and Templ 2013a) for the open source statistical computing environment R (R Development Core Team 2013). It provides functionality for standard and robust estimation of indicators on social exclusion and poverty from complex survey samples. The aim of the paper is to present the most important functionality of the package.

A more complete overview of the available functionality is given in additional package vignettes on specialized topics. A list of the available vignettes can be viewed from within R with the following command:

```
R> vignette(package="laeken")
```

Even though official statistical agencies usually rely on commercial software, R has gained some traction in the survey statistics community over the years. Various add-on packages for survey methodology are now available. For instance, an extensive collection of methods for the analysis of survey samples is implemented in package **survey** (Lumley 2004, 2012). The accompanying book by Lumley (2010) also serves as an excellent introduction to survey statistics with R. Other examples for more specialized functionality are package **sampling** (Tillé and Matei 2012) for finite population sampling, and package **EVER** (Zardetto 2012) for variance estimation based on efficient resampling. For the common problem of nonresponse, package **VIM** (Templ, Alfons, Kowarik, and Prantner 2013) allows to explore the structure of missing data via visualization techniques (see Templ, Alfons, and Filzmoser 2012), and to impute the missing values via advanced imputation methods (e.g., Templ, Kowarik, and Filzmoser 2011). Even a general framework for simulation studies in survey statistics is available through package **simFrame** (Alfons, Templ, and Filzmoser 2010; Alfons 2012).

Package **laeken** provides functionality for the estimation of indicators that is not available in any of the packages listed above, including a novel approach for robust estimation of indicators. While packages **survey** and **EVER** require the generation of certain objects describing the survey design prior to analysis, the methods in **laeken** can be directly applied to the data. This allows **laeken** to be used more efficiently in simulations, for instance with the **simFrame** framework. Furthermore, **laeken** can easily be used on samples drawn with the **sampling** package or preprocessed with the **VIM** package.

The rest of the paper is organized as follows. Section 2 introduces the data sets that are used in the examples throughout the paper. In Section 3, the most widely used indicators on social exclusion and poverty are briefly described. The basic design of the package and its core functionality are then presented in Section 4. More advanced topics such as robust

estimation and variance estimation via bootstrap techniques are discussed in Sections 5 and 6, respectively. The final Section 7 concludes.

## 2. Data sets

Package **laeken** contains example data sets for two well-known surveys: the *European Union Statistics on Income and Living Conditions* (EU-SILC) and the *Structure of Earnings Survey* (SES). Since original data from those surveys are confidential, the example data sets are simulated using the methodology described in Alfons, Kraft, Templ, and Filzmoser (2011) and implemented in the R package **simPopulation** (Alfons and Kraft 2012). Such close-to-reality data sets provide nearly the same multivariate structure as the confidential original data sets and allow researchers to test and compare methods. However, for policy making purposes and economic interpretation, estimations need to be based on the original data. In any case, the simulated data sets are used in the code examples throughout the paper.

### 2.1. European Union Statistics on Income and Living Conditions

EU-SILC is an annual household survey conducted in EU member states and other European countries. Samples consist of about 450 variables containing information on demographics, income and living conditions (see Eurostat 2004b). Most notably, EU-SILC serves as data basis for measuring risk-of-poverty and social cohesion in Europe. A subset of the indicators computed from EU-SILC is presented in Section 3.2.

The EU-SILC example data set in **laeken** is called `eusilc` and contains 14 827 observations from 6 000 households on the 28 most important variables. The data are synthetically generated from preprocessed Austrian EU-SILC data from 2006 provided by Statistics Austria. A description of all the variables is given in the R help page of the data set. To give an overview of what the data look like, the first three observations of the first ten variables of `eusilc` are printed below.

```
R> data("eusilc")
R> head(eusilc[, 1:10], 3)
```

	db030	hsize	db040	rb030	age	rb090	p1030	pb220a	py010n	py050n
1	1	3	Tyrol	101	34	female	2	AT	9756.25	0
2	1	3	Tyrol	102	39	male	1	Other	12471.60	0
3	1	3	Tyrol	103	2	male	<NA>	<NA>	NA	NA

For this paper, the variable `eqIncome` (equivalized disposable income) is of main interest. Other variables are in some cases used to break down the data into different demographics in order to estimate the indicators on those subsets.

### 2.2. Structure of Earnings Survey

The Structure of Earnings Survey (SES) (Eurostat 2006) is an enterprise survey that aims at providing harmonized data on earnings for almost all European countries. SES data not only contain information on the enterprise level, but also on the individual employment level from

a large sample of employees. The most important indicator on the basis of SES data is the gender pay gap, which is described in Section 3.3.

The SES example data set in **laeken** is called **ses** and contains information on 27 variables and 15 691 employees from 500 places of work. It is a subset of synthetic data that are simulated from preprocessed Austrian SES 2006 data provided by Statistics Austria. The first three observations of the first seven variables are shown below.

```
R> data("ses")
R> head(ses[, 1:7], 3)
```

	location	NACE1	size	economicFinanc	payAgreement	IDunit	sex
112	AT3	C-Mining	E1000	B	B	81461	male
111	AT3	C-Mining	E1000	B	B	81461	male
114	AT3	C-Mining	E1000	B	B	81461	male

In this paper, the SES data is used to illustrate the estimation of the gender pay gap. Hence the most important variables for our purposes are **earningsHour**, **sex** and **education**. For a description of all the variables in the data set, the reader is referred to its R help page.

### 3. Indicators

This section gives a brief description of the most widely used indicators on poverty, social cohesion and gender differences. Unless otherwise stated, the presented definitions strictly follow Eurostat (2004a, 2009). While quick examples for their computation are provided in this section, a detailed discussion on the respective functions is given later on in Section 4.

#### 3.1. Weighted median and quantile estimation

Nearly all of the indicators considered in the paper require the estimation of the median income or other quantiles of the income distribution. Note that in the analysis of income distributions, the median income is of higher interest than the arithmetic mean, since income distributions typically are strongly right-skewed.

In mathematical terms, quantiles are defined as  $q_p := F^{-1}(p)$ , where  $F$  is the distribution function on the population level and  $0 \leq p \leq 1$ . The median as an important special case is given by  $p = 0.5$ . For the following definitions, let  $n$  be the number of observations in the sample, let  $\mathbf{x} := (x_1, \dots, x_n)^\top$  denote the income with  $x_1 \leq \dots \leq x_n$ , and let  $\mathbf{w} := (w_1, \dots, w_n)^\top$  be the corresponding sample weights. Weighted quantiles for the estimation of the population values are then given by

$$\hat{q}_p = \hat{q}_p(\mathbf{x}, \mathbf{w}) := \begin{cases} \frac{1}{2}(x_j + x_{j+1}), & \text{if } \sum_{i=1}^j w_i = p \sum_{i=1}^n w_i, \\ x_{j+1}, & \text{if } \sum_{i=1}^j w_i < p \sum_{i=1}^n w_i < \sum_{i=1}^{j+1} w_i. \end{cases} \quad (1)$$

#### 3.2. Indicators on social exclusion and poverty

The indicators described in this section are estimated from EU-SILC data based on household income rather than personal income. For each person, this *equivalized disposable income* is

defined as the total household disposable income divided by the equivalized household size. It follows that each person in the same household receives the same equivalized disposable income. The total disposable income of a household is thereby calculated by adding together the personal income received by all of the household members plus the income received at the household level. The equivalized household size is defined according to the modified OECD scale, which gives a weight of 1.0 to the first adult, 0.5 to other household members aged 14 or over, and 0.3 to household members aged less than 14.

For the definitions of the following indicators, let  $\mathbf{x} := (x_1, \dots, x_n)^\top$  be the equivalized disposable income with  $x_1 \leq \dots \leq x_n$  and let  $\mathbf{w} := (w_1, \dots, w_n)^\top$  be the corresponding sample weights, where  $n$  denotes the number of observations. Furthermore, define the following index sets for a certain threshold  $t$ :

$$I_{<t} := \{i \in \{1, \dots, n\} : x_i < t\}, \quad (2)$$

$$I_{\leq t} := \{i \in \{1, \dots, n\} : x_i \leq t\}, \quad (3)$$

$$I_{>t} := \{i \in \{1, \dots, n\} : x_i > t\}. \quad (4)$$

#### *At-risk-at-poverty rate*

In order to define the *at-risk-of-poverty rate* (ARPR), the *at-risk-of-poverty threshold* (ARPT) needs to be introduced first, which is set at 60% of the national median equivalized disposable income. Then the at-risk-at-poverty rate is defined as the proportion of persons with an equivalized disposable income below the at-risk-at-poverty threshold. In a more mathematical notation, the at-risk-at-poverty rate is defined as

$$ARPR := P(x < 0.6 \cdot q_{0.5}) \cdot 100, \quad (5)$$

where  $q_{0.5} := F^{-1}(0.5)$  denotes the population median (50% quantile) and  $F$  is the distribution function of the equivalized income on the population level.

For the estimation of the at-risk-at-poverty rate from a sample, first the at-risk-at-poverty threshold is estimated by

$$\widehat{ARPT} = 0.6 \cdot \hat{q}_{0.5}, \quad (6)$$

where  $\hat{q}_{0.5}$  is the weighted median as defined in Equation 1. Then the at-risk-at-poverty rate can be estimated by

$$\widehat{ARPR} := \frac{\sum_{i \in I_{<\widehat{ARPT}}} w_i}{\sum_{i=1}^n w_i} \cdot 100, \quad (7)$$

where  $I_{<\widehat{ARPT}}$  is an index set of persons with an equivalized disposable income below the estimated at-risk-of-poverty threshold as defined in Equation 2.

In package **laeken**, the function `arpr()` is implemented to estimate the at-risk-at-poverty rate.

```
R> arpr("eqIncome", weights = "rb050", data = eusilc)
```

Value:

```
[1] 14.44422
```

Threshold:

```
[1] 10859.24
```

Note that the at-risk-of-poverty threshold is computed internally by `arpr()`. If necessary, it can also be computed by the user through function `arpt()`.

In addition, a highly related indicator is the *dispersion around the at-risk-of-poverty threshold*, which is defined as the proportion of persons with an equivalized disposable income below 40%, 50% and 70% of the national weighted median equivalized disposable income. For the estimation of this indicator with function `arpr()`, the proportion of the median equivalized income to be used can easily be adjusted via the argument `p`.

```
R> arpr("eqIncome", weights = "rb050", p = c(0.4, 0.5, 0.7), data = eusilc)
```

Value:

40%	50%	70%
4.766885	7.988134	21.856379

Threshold:

40%	50%	70%
7239.491	9049.363	12669.109

### *Quintile share ratio*

The income *quintile share ratio* (QSR) is defined as the ratio of the sum of the equivalized disposable income received by the 20% of the population with the highest equivalized disposable income to that received by the 20% of the population with the lowest equivalized disposable income.

For a given sample, let  $\hat{q}_{0.2}$  and  $\hat{q}_{0.8}$  denote the weighted 20% and 80% quantiles, respectively, as defined in Equation 1. Using index sets  $I_{\leq \hat{q}_{0.2}}$  and  $I_{> \hat{q}_{0.8}}$  as defined in Equations 3 and 4, respectively, the quintile share ratio is estimated by

$$\widehat{QSR} := \frac{\sum_{i \in I_{> \hat{q}_{0.8}}} w_i x_i}{\sum_{i \in I_{\leq \hat{q}_{0.2}}} w_i x_i}. \quad (8)$$

To estimate the quintile share ratio, the function `qsr()` is available.

```
R> qsr("eqIncome", weights = "rb050", data = eusilc)
```

Value:

```
[1] 3.970004
```

### *Relative median at-risk-of-poverty gap*

The *relative median at-risk-of-poverty gap* (RMPG) is given by the difference between the median equivalized disposable income of persons below the at-risk-of-poverty threshold and the at-risk of poverty threshold itself, expressed as a percentage of the at-risk-of-poverty threshold.

For the estimation of the relative median at-risk-of-poverty gap from a sample, let  $\widehat{ARPT}$  be the estimated at-risk-of-poverty threshold according to Equation 6, and let  $I_{< \widehat{ARPT}}$  be

an index set of persons with an equivalized disposable income below the estimated at-risk-of-poverty threshold as defined in Equation 2. Using this index set, define  $\mathbf{x}_{<\widehat{ARPT}}$  :=  $(x_i)_{i \in I_{<\widehat{ARPT}}}$  and  $\mathbf{w}_{<\widehat{ARPT}}$  :=  $(w_i)_{i \in I_{<\widehat{ARPT}}}$ . Furthermore, let  $\hat{q}_{0.5}(\mathbf{x}_{<\widehat{ARPT}}, \mathbf{w}_{<\widehat{ARPT}})$  be the corresponding weighted median according to the definition in Equation 1. Then the relative median at-risk-of-poverty gap is estimated by

$$\widehat{RMPG} = \frac{\widehat{ARPT} - \hat{q}_{0.5}(\mathbf{x}_{<\widehat{ARPT}}, \mathbf{w}_{<\widehat{ARPT}})}{\widehat{ARPT}} \cdot 100. \quad (9)$$

The relative median at-risk-of-poverty gap is implemented in the function `rmpg()`.

```
R> rmpg("eqIncome", weights = "rb050", data = eusilc)
```

Value:

```
[1] 18.9286
```

Threshold:

```
[1] 10859.24
```

### *Gini coefficient*

The *Gini coefficient* is defined as the relationship of cumulative shares of the population arranged according to the level of equivalized disposable income, to the cumulative share of the equivalized total disposable income received by them.

Mathematically speaking, the Gini coefficient is estimated from a sample by

$$\widehat{Gini} := 100 \left[ \frac{2 \sum_{i=1}^n (w_i x_i \sum_{j=1}^i w_j) - \sum_{i=1}^n w_i^2 x_i}{(\sum_{i=1}^n w_i) \sum_{i=1}^n (w_i x_i)} - 1 \right]. \quad (10)$$

For estimating the Gini coefficient, the function `gini()` can be used.

```
R> gini("eqIncome", weights = "rb050", data = eusilc)
```

Value:

```
[1] 26.48962
```

### 3.3. The gender pay gap

Probably the most important indicator derived from the SES data is the *gender pay gap* (GPG). The calculation of the gender pay gap is based on each person's hourly earnings, which are given by the gross monthly earnings from employment divided by the number of hours usually worked per week in employment during 4.33 weeks. The gender pay gap in unadjusted form is then defined as the difference between average gross earnings of male paid employees and of female paid employees divided by the earnings of male paid employees (Eurostat 2004a). Further discussion on the gender pay gap in Europe can be found in, e.g., Beblot, Beniger, Heinze, and Laisney (2003).

For the following definitions, let  $\mathbf{x} := (x_1, \dots, x_n)^\top$  be the hourly earnings with  $x_1 \leq \dots \leq x_n$ , where  $n$  is the number of observations. As in the previous sections,  $\mathbf{w} := (w_1, \dots, w_n)^\top$  denotes the corresponding sample weights. Then define the index set

$$I_M := \{i \in \{1, \dots, n\} : \text{worked as least 1 hour per week} \wedge (16 \leq \text{age} \leq 65) \wedge \text{person is male}\},$$

and define  $I_F$  analogously as the index set which differs from  $I_M$  in the fact that it includes females instead of males. With these index sets, the gender pay gap in unadjusted form is estimated by

$$GPG_{(mean)} = \left( \frac{\sum_{i \in I_M} w_i x_i}{\sum_{i \in I_M} w_i} - \frac{\sum_{i \in I_F} w_i x_i}{\sum_{i \in I_F} w_i} \right) / \frac{\sum_{i \in I_M} w_i x_i}{\sum_{i \in I_M} w_i}. \quad (11)$$

The function `gpg()` is implemented in **laeken** to estimate the gender pay gap.

```
R> gpg("earningsHour", gender = "sex", weights = "weights",
+      data = ses)
```

```
Value:
[1] 0.2517759
```

While Eurostat (2004a) proposes the weighted mean as a measure for the average in the definition of the gender pay gap, the U.S. Census Bureau uses the weighted median to better reflect the average in skewed earnings distributions (see, e.g., Weinberg 2007). In this case, the estimate of the gender pay gap in unadjusted form changes to

$$GPG_{(med)} = \frac{\hat{q}_{0.5}(\mathbf{x}_{I_M}) - \hat{q}_{0.5}(\mathbf{x}_{I_F})}{\hat{q}_{0.5}(\mathbf{x}_{I_M})}, \quad (12)$$

where  $\mathbf{x}_{I_M} := (x_i)_{i \in I_M}$  and  $\mathbf{x}_{I_F} := (x_i)_{i \in I_F}$ .

It should be noted that even though Eurostat proposes to estimate the gender pay gap via weighted means, Statistics Austria for example uses the variant based on weighted medians as well.

In function `gpg()`, using the weighted median rather than the weighted mean can be specified via the `method` argument.

```
R> gpg("earningsHour", gender = "sex", weights = "weights",
+      data = ses, method = "median")
```



```
Value:
[1] 0.2298387
```

## 4. Basic design and core functionality

This section discusses the basic design of package **laeken** and its core functions for the estimation of indicators.

### 4.1. Indicators and class structure

Small examples for computing the social exclusion and poverty indicators with package **laeken** were already shown in Section 3. These functions are now discussed in detail. As a reminder, the following indicators are implemented in the package:

`arpr()` for the at-risk-of-poverty rate, as well as the dispersion around the at-risk-of-poverty threshold.

`qsr()` for the quintile share ratio.

`rmpg()` for the relative median at-risk-of-poverty gap.

`gini()` for the gini coefficient.

`gpg()` for the gender pay gap.

All these functions have a very similar interface and allow to compute point and variance estimates with a single command, even for different subdomains of the data. Most importantly, the user can supply character strings specifying the household income via the first argument and the sample weights via the `weights` argument. The data are then taken from the data frame passed as the `data` argument.

```
R> gini("eqIncome", weights = "rb050", data = eusilc)
```

```
Value:
[1] 26.48962
```

Alternatively, the user can supply the data directly as vectors:

```
R> gini(eusilc$eqIncome, weights = eusilc$rb050)
```

```
Value:
[1] 26.48962
```

For a full list of arguments, the reader is referred to the R help page of the corresponding function.

Package **laeken** follows an object-oriented design using S3 classes (Chambers and Hastie 1992). Thus each of the above functions returns an object of a certain class for the respective indicator. All those classes thereby inherit from the class `"indicator"`.

Among other information, the basic class `"indicator"` contains the following components:

**value:** the point estimate.

**valueByStratum:** a data frame containing the point estimates for each domain.

**var:** the variance estimate.

**varByStratum:** a data frame containing the variance estimates for each domain.

**ci:** the confidence interval.

**ciByStratum:** a data frame containing the confidence intervals for each domain.

All indicators inherit the components of class "**indicator**", as well as the methods that are defined for this basic class, which has the advantage that code can be shared among the set of indicators. However, each indicator also has its own class such that methods unique to the indicator can be defined. Following a common convention for **S3** classes, the classes for the indicators have the same names as the functions for computing them. Hence the following classes are implemented in package **laeken**:

- Class "**arpr**" with the following additional components:
  - p:** the percentage of the weighted median used for the at-risk-of-poverty threshold.
  - threshold:** the at-risk-of-poverty threshold.
- Class "**qsr**" with no additional components.
- Class "**rmpg**" with the following additional components:
  - threshold:** the at-risk-of-poverty threshold.
- Class "**gini**" with no additional components.
- Class "**gpg**" with no additional components.

Furthermore, functions to test whether an object is a member of the basic class or one of the subclasses are available. The function to test for the basic class is called `is.indicator()`. Similarly, the functions to test for the subclasses are called `is.foo()`, where `foo` is the name of the corresponding class (e.g., `is.arpr()`).

## 4.2. Estimating the indicators in subdomains

One of the most important features of **laeken** is that indicators can easily be evaluated for different subdomains. These can be regions, but also any other breakdown given by a categorical variable, for instance age categories or gender. All the user needs to do is to specify such a categorical variable via the **breakdown** argument. Note that for the at-risk-of-poverty rate and relative median at-risk-of-poverty gap, the same overall at-risk-of-poverty threshold is used for all subdomains (see [Eurostat 2004a, 2009](#)).

In the following example, the overall estimate for the at-risk-of-poverty rate is computed together with more regional estimates.

```
R> a <- arpr("eqIncome", weights = "rb050", breakdown = "db040",
+          data = eusilc)
R> a
```

```
Value:
[1] 14.44422
```

```
Value by domain:
      stratum  value
1  Burgenland 19.53984
2  Carinthia 13.08627
3 Lower Austria 13.84362
4  Salzburg 13.78734
5  Styria 14.37464
6  Tyrol 15.30819
7 Upper Austria 10.88977
8  Vienna 17.23468
9  Vorarlberg 16.53731
```

```
Threshold:
[1] 10859.24
```

### 4.3. Extracting information using the `subset()` method

If estimates of an indicator have been computed for several subdomains, extracting a subset of the results for some domains of particular interest can be done with the corresponding `subset()` method. For example, the following command extracts the estimates of the at-risk-of-poverty rate for the regions Lower Austria and Vienna from the object computed above.

```
R> subset(a, strata = c("Lower Austria", "Vienna"))
```

```
Value:
[1] 14.44422
```

```
Value by domain:
      stratum  value
3 Lower Austria 13.84362
8  Vienna 17.23468
```

```
Threshold:
[1] 10859.24
```

It is thereby worth pointing out that not every indicator needs its own `subset()` method due to inheritance from the basic class `"indicator"`.

## 5. Robust estimation

In economic data, variables such as income are typically heavy-tailed and may contain outliers. To identify extreme outliers, we model heavy tails with a Pareto distribution. In the survey setting, the upper tail of the population values are assumed to follow a Pareto distribution. The **laeken** package includes recently developed methods of [Alfons, Templ, and Filzmoser \(2013b\)](#) that allow sampling weights to be incorporated into the Pareto model estimation. In the remainder of the section, we briefly outline the methodology and demonstrate how it can be implemented with the **laeken** package.

### 5.1. Pareto distribution

The *Pareto distribution* is defined in terms of its cumulative distribution function

$$F_{\theta}(x) = 1 - \left(\frac{x}{x_0}\right)^{-\theta}, \quad x \geq x_0, \quad (13)$$

where  $x_0 > 0$  is the scale parameter and  $\theta > 0$  is the shape parameter ([Kleiber and Kotz 2003](#)). Furthermore, its density function is given by

$$f_{\theta}(x) = \frac{\theta x_0^{\theta}}{x^{\theta+1}}, \quad x \geq x_0. \quad (14)$$

Clearly, the Pareto distribution is a highly right-skewed distribution with a heavy tail.

In Pareto tail modeling, the cumulative distribution function on the whole range of  $x$  is then modeled as

$$F(x) = \begin{cases} G(x), & \text{if } x \leq x_0, \\ G(x_0) + (1 - G(x_0))F_{\theta}(x), & \text{if } x > x_0, \end{cases} \quad (15)$$

where  $G$  is an unknown distribution function ([Dupuis and Victoria-Feser 2006](#)). For a given survey sample, let  $\mathbf{x} = (x_1, \dots, x_n)^{\top}$  be the observed values of the variable of interest with  $x_1 \leq \dots \leq x_n$  and  $\mathbf{w} := (w_1, \dots, w_n)^{\top}$  the corresponding sample weights, where  $n$  denotes the total number of observations. In addition, let  $k$  denote the number of observations to be used for tail modeling. Note that the estimation of  $x_0$  and  $k$  directly correspond with each other. If  $k$  is fixed, the threshold is estimated by  $\hat{x}_0 = x_{n-k}$ . If in turn an estimate  $\hat{x}_0$  is obtained,  $k$  is given by the number of observations that are larger than  $\hat{x}_0$ .

In this section, we focus on the EU-SILC example data, where the equivalized disposable income is the main variable of interest. To illustrate the robustness of the presented methods, we replace the equivalized disposable income of the household with the highest income with a large outlier. Note that the resulting income vector is stored in a new variable.

```
R> hID <- eusilc$db030[which.max(eusilc$eqIncome)]
R> eqIncomeOut <- eusilc$eqIncome
R> eqIncomeOut[eusilc$db030 == hID] <- 10000000
```

Moreover, since the equivalized disposable income is a form of household income, the Pareto distribution needs to be modeled on the household level rather than the personal level. Thus we create a data set that only contains the equivalized disposable income with the outlier and the sample weights on the household level.

```
R> keep <- !duplicated(eusilc$db030)
R> eusilcH <- data.frame(eqIncome=eqIncomeOut, db090=eusilc$db090)[keep,]
```

## 5.2. Pareto quantile plot and finding the threshold

The first step in any practical analysis should be to explore the data with visualization techniques. For our purpose, the *Pareto quantile plot* is a powerful tool to check whether the Pareto model is appropriate. The plot was introduced by [Beirlant, Vynckier, and Teugels \(1996\)](#) for the case without sample weights, and adapted to take sample weights into account by [Alfons et al. \(2013b\)](#).

The idea behind the Pareto quantile plot is that under the Pareto model, there exists a linear relationship between the logarithms of the observed values and the quantiles of the standard exponential distribution. For survey samples, the observed values are therefore plotted against the quantities

$$-\log \left( 1 - \frac{\sum_{j=1}^i w_j}{\sum_{j=1}^n w_j} \frac{n}{n+1} \right), \quad i = 1, \dots, n. \quad (16)$$

When all sample weights are equal, the correction factor  $n/(n+1)$  ensures that Equation 16 reduces to the theoretical quantiles taken on the  $n$  inner grid points from  $n+1$  equally sized subsets of the interval  $[0, 1]$  (see [Alfons et al. 2013b](#), for details).

In package `laeken`, the Pareto quantile plot is implemented in the function `paretoQPlot()`. Figure 1 shows the resulting plot for the EU-SILC example data on the household level. Since the tail of the data forms almost a straight line, the Pareto tail model is suitable for the data at hand.

Moreover, Figure 1 illustrates the two main advantages that make the Pareto quantile plot so powerful. First, nonrepresentative outliers (i.e., extremely large observations that deviate from the Pareto model) are clearly visible. In our example, the outlier that we introduced into the data set is located far away from the rest of the data in the top right corner of the plot. Second, the leftmost point of a fitted line in the tail of the data can be used as an estimate of the threshold  $x_0$  in the Pareto model, i.e., the scale parameter of fitted Pareto distribution. The slope of the fitted line is then in turn an estimate of  $1/\theta$ , the reciprocal of the shape parameter. A disadvantage of this graphical method to determine the parameters of the fitted Pareto distribution is of course that it is not very exact.

Nevertheless, the function `paretoQPlot()` allows the user to select the threshold in the Pareto model interactively by clicking on a data point. Information on the selected threshold is thereby printed on the R console. This process can be repeated until the user terminates the interactive session, typically by a secondary mouse click. Then the selected threshold is returned as an object of class `"paretoScale"`, which consists of the component `x0` for the threshold (scale parameter) and the component `k` for the number of observations in the tail (i.e., larger than the threshold).

### *Van Kerm's rule of thumb*

For EU-SILC data, [Van Kerm \(2007\)](#) developed a formula for the threshold  $x_0$  in the Pareto model that has more of a rule-of-thumb nature. It is given by

$$\hat{x}_0 := \min(\max(2.5\bar{x}, \hat{q}_{0.98}), \hat{q}_{0.97}), \quad (17)$$

```
R> paretoQPlot(eusilch$eqIncome, w = eusilch$db090)
```

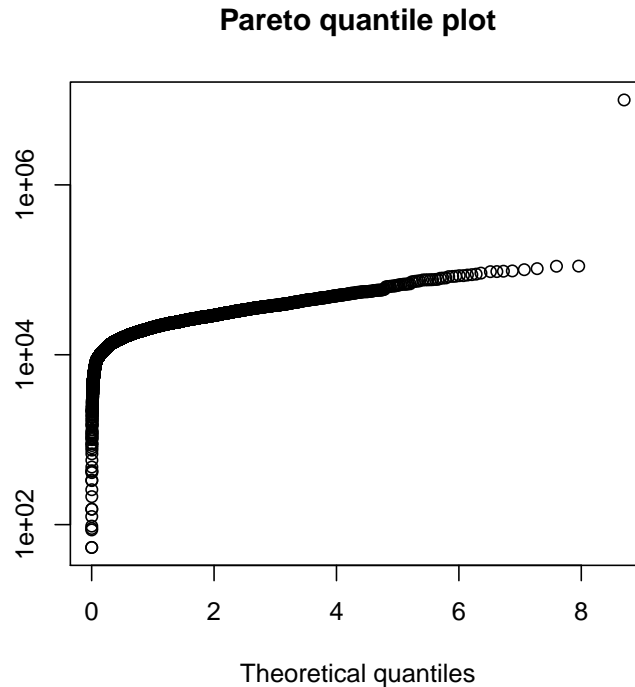


Figure 1: Pareto quantile plot for the EU-SILC example data on the household level with the largest observation replaced by an outlier.

where  $\bar{x}$  is the weighted mean, and  $\hat{q}_{0.98}$  and  $\hat{q}_{0.97}$  are weighted quantiles as defined in Equation 1. It is important to note that this formula is designed specifically for the equalized disposable income in EU-SILC data and can withstand a small number of nonrepresentative outliers.

In **laeken**, the function `paretoScale()` provides functionality for estimating the threshold via Van Kerm's formula. Its argument `w` can be used to supply sample weights.

```
R> ts <- paretoScale(eusilch$eqIncome, w = eusilch$db090)
R> ts
```

```
Threshold: 48459.43
```

```
Number of observations in the tail: 119
```

The estimated threshold is again returned as an object of class "paretoScale".

### 5.3. Estimation of the shape parameter

Once the threshold for the Pareto model is determined, the shape parameter  $\theta$  can be estimated via the *points over threshold* method, i.e., by fitting the distribution to the  $k$  data

points that are larger than the threshold. Since our aim is to identify extreme outliers that deviate from the Pareto model, the shape parameter needs to be estimated in a robust way.

### *Integrated squared error estimator*

The integrated squared error (ISE) criterion was first introduced by Terrell (1990) as a more robust alternative to maximum likelihood estimation. Vandewalle, Beirlant, Christmann, and Hubert (2007) proposed to use this criterion in the context of Pareto tail modeling, but they do not consider sample weights. However, the Pareto distribution is modeled in terms of the *relative excesses*

$$y_i := \frac{x_{n-k+i}}{x_{n-k}}, \quad i = 1, \dots, k. \quad (18)$$

Now the density function of the Pareto distribution for the relative excesses is approximated by

$$f_\theta(y) = \theta y^{-(1+\theta)}. \quad (19)$$

With this model density, the integrated squared error criterion can be written as

$$\hat{\theta} = \arg \min_{\theta} \left[ \int f_\theta^2(y) dy - 2\mathbb{E}(f_\theta(Y)) \right], \quad (20)$$

see Vandewalle *et al.* (2007). For survey samples, Alfons *et al.* (2013b) propose to use the weighted mean as an estimator of  $\mathbb{E}(f_\theta(Y))$  to obtain the *weighted integrated squared error* (wISE) estimator:

$$\hat{\theta}_{\text{wISE}} = \arg \min_{\theta} \left[ \int f_\theta^2(y) dy - \frac{2}{\sum_{i=1}^k w_{n-k+i}} \sum_{i=1}^k w_{n-k+i} f_\theta(y_i) \right]. \quad (21)$$

The wISE estimator can be computed using the function `thetaISE()`. The arguments `k` and `x0` are available to supply either the number of observations in the tail or the threshold, and sample weights can be supplied via the argument `w`.

```
R> thetaISE(eusilch$eqIncome, k = ts$k, w = eusilch$db090)
```

```
[1] 3.993801
```

```
R> thetaISE(eusilch$eqIncome, x0 = ts$x0, w = eusilch$db090)
```

```
[1] 3.993801
```

### *Partial density component estimator*

Following the observation by Scott (2004) that  $f_\theta$  in the ISE criterion does not need to be a real density, Vandewalle *et al.* (2007) proposed to minimize the ISE criterion based on an incomplete density mixture model  $uf_\theta$  instead. Alfons *et al.* (2013b) generalized their estimator to take sample weights into account, yielding the *weighted partial density component* (wPDC) estimator

$$\hat{\theta}_{\text{wPDC}} = \arg \min_{\theta} \left[ u^2 \int f_\theta^2(y) dy - \frac{2u}{\sum_{i=1}^k w_{n-k+i}} \sum_{i=1}^k w_{n-k+i} f_\theta(y_i) \right] \quad (22)$$

with

$$\hat{u} = \frac{1}{\sum_{i=1}^k w_{n-k+i}} \sum_{i=1}^k w_{n-k+i} f_{\hat{\theta}}(y_i) \bigg/ \int f_{\hat{\theta}}^2(y) dy. \quad (23)$$

Based on extensive simulation studies, [Alfons \*et al.\* \(2013b\)](#) conclude that the wPDC estimator is favorable over the wISE estimator due to better robustness properties.

The function `thetaPDC()` is implemented in package `laeken` to compute the wPDC estimator. As before, it is necessary to supply either the number of observations in the tail via the argument `k`, or the threshold via the argument `x0`. Sample weights can be supplied using the argument `w`.

```
R> thetaPDC(eusilCH$eqIncome, k = ts$k, w = eusilCH$db090)
```

```
[1] 4.132596
```

```
R> thetaPDC(eusilCH$eqIncome, x0 = ts$x0, w = eusilCH$db090)
```

```
[1] 4.132596
```

#### 5.4. Robust estimation of the indicators via Pareto tail modeling

The basic idea for robust estimation of the indicators is to first detect nonrepresentative outliers based on the Pareto model. Afterwards their influence on the indicators is reduced by either downweighting the outliers and recalibrating the remaining observations, or by replacing the outlying values with values from the fitted distribution. The main advantage of this general approach is that it can be applied to any indicator.

With the fitted Pareto distribution  $F_{\hat{\theta}}$ , nonrepresentative outliers can now be detected as observations being larger than a certain  $F_{\hat{\theta}}^{-1}(1 - \alpha)$  quantile. From extensive simulation studies ([Hulliger \*et al.\* 2011](#); [Alfons \*et al.\* 2013b](#)),  $\alpha = 0.005$  or  $\alpha = 0.01$  are seem suitable choices for this tuning parameter. Then the following approaches are implemented in `laeken` to reduce the influence of the outliers:

**Calibration of nonrepresentative outliers (CN):** As nonrepresentative outliers are considered to be somewhat unique to the population data, the sample weights of the corresponding observations are set to 1. The weights of the remaining observations are adjusted accordingly by calibration (see, e.g., [Deville, Särndal, and Sautory 1993](#)).

**Replacement of nonrepresentative outliers (RN):** The outliers are replaced by values drawn from the fitted distribution  $F_{\hat{\theta}}$ , thereby preserving the order of the original values.

**Shrinkage of nonrepresentative outliers (SN):** The outliers are shrunken to the theoretical quantile  $F_{\hat{\theta}}^{-1}(1 - \alpha)$  used for outlier detection.

A more mathematical formulation and further details on the CN and RN approaches can be found in [Alfons \*et al.\* \(2013b\)](#), who advocate the CN approach in combination with the wPDC estimator for fitting the Pareto distribution.



```
R> plot(fit)
```

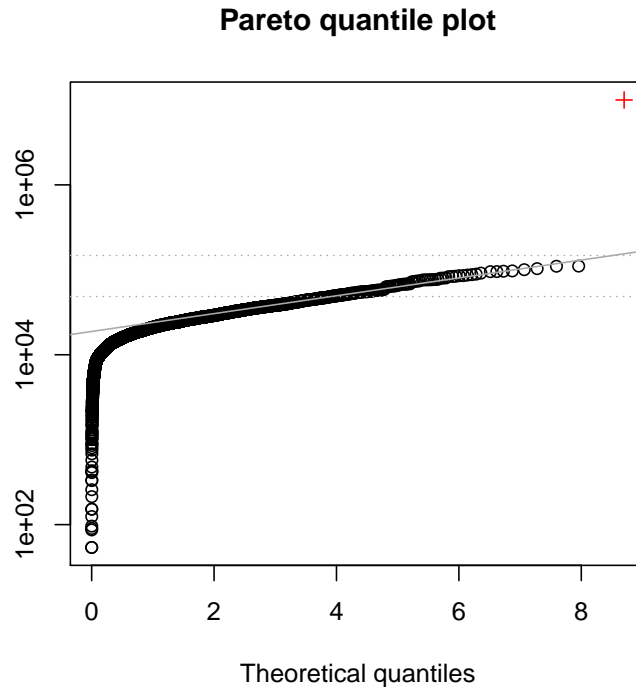


Figure 2: Pareto quantile plot for the EU-SILC example data with additional diagnostic information on the fitted distribution and any detected outliers.

For a practical analysis with package **laeken**, let us first revisit the estimation of the shape parameter. Rather than applying a function such as `thetaPDC()` directly as in the previous section, the function `paretoTail()` should be used to fit the Pareto distribution to the upper tail of the data. It returns an object of class "paretoTail", which contains all necessary information for further analysis with one of the approaches described above.

```
R> fit <- paretoTail(eqIncomeOut, k = ts$k, w = eusilc$db090,
+   groups = eusilc$db030)
```

Note that the household IDs are supplied via the argument `groups` such that the Pareto distribution is fitted on the household level rather than the individual level. By default, the wPDC is used to estimate the shape parameter, but other estimators can be specified via the `method` argument. In addition, the tuning parameter  $\alpha$  for outlier detection can be supplied as argument `alpha`.

Moreover, the `plot()` method for "paretoTail" objects produces a Pareto quantile plot (see Section 5.2) with additional diagnostic information. Figure 2 contains the resulting plot for the object computed above. The lower horizontal dotted line corresponds to the estimated threshold  $\hat{x}_0$ , whereas the slope of the solid grey line is given by the reciprocal of the estimated shape parameter  $\hat{\theta}$ . Furthermore, the upper horizontal dotted line represents the theoretical

quantile used for outlier detection. In this example, the threshold seems somewhat too high. Nevertheless, the estimate of the shape parameter is accurate and the cutoff point for outlier detection is appropriate, resulting in correct identification of the outlier that we added to the data set.

For downweighting nonrepresentative outliers, the function `reweightOut()` is available. It returns a vector of the recalibrated weights. In the command below, we use regional information as auxiliary variables for calibration. The function `calibVars()` thereby transforms a factor into a matrix of binary variables. The returned recalibrated weights are then simply used to estimate the Gini coefficient with function `gini()`.

```
R> w <- reweightOut(fit, calibVars(eusilc$db040))
R> gini(eqIncomeOut, w)
```

Value:

```
[1] 26.45973
```

To replace the nonrepresentative outliers with values drawn from the fitted distribution, the function `replaceOut()` is implemented. For reproducible results, the seed of the random number generator is set beforehand. The returned income vector is then supplied to `gini()` to estimate the Gini coefficient.

```
R> set.seed(123)
R> eqIncomeRN <- replaceOut(fit)
R> gini(eqIncomeRN, weights = eusilc$rb050)
```

Value:

```
[1] 26.4645
```

Similarly, the function `shrinkOut()` can be used to shrink the nonrepresentative outliers to the theoretical quantile used for outlier detection.

```
R> eqIncomeSN <- shrinkOut(fit)
R> gini(eqIncomeSN, weights = eusilc$rb050)
```

Value:

```
[1] 26.48831
```

All three robust estimates are very close to the original value before the outlying household had been introduced (see Section 3.2). For comparison, we compute the standard estimate of Gini coefficient with the income vector including the outlying household.

```
R> gini(eqIncomeOut, weights = eusilc$rb050)
```

Value:

```
[1] 29.24333
```

Clearly, the standard estimate shows an unreasonably large influence of only one outlying household, illustrating the need for the robust methods.

## 6. Variance estimation

The **laeken** package uses bootstrap techniques for estimating the variance of complex survey indicators. Bootstrap methods in general provide better estimates for nonsmooth estimators than other other resampling techniques such as jackknifing or balanced repeated replication (e.g., Bruch, Münnich, and Zins 2011). The naive bootstrap in **laeken** is quite fast to compute and provides reasonable estimates whenever there is not much variation in the sample weights, which is for example typically the case for EU-SILC data. If there is larger variation among the sample weights, a calibrated bootstrap should be applied. We describe both approaches and their implementation in the following sections.

### 6.1. Naive bootstrap

Let  $\tau$  denote a certain indicator of interest and let  $\mathbf{X} := (\mathbf{x}_1, \dots, \mathbf{x}_n)^\top$  be a survey sample with  $n$  observations. Then the *naive bootstrap* algorithm for estimating the variance and confidence interval of an estimate  $\hat{\tau}(\mathbf{X})$  of the indicator can be summarized as follows:

1. Draw  $R$  independent bootstrap samples  $\mathbf{X}_1^*, \dots, \mathbf{X}_R^*$  from  $\mathbf{X}$ . For stratified sampling designs, resampling is performed within each stratum independently.
2. Compute the bootstrap replicate estimates  $\hat{\tau}_r^* := \hat{\tau}(\mathbf{X}_r^*)$  for each bootstrap sample  $\mathbf{X}_r^*$ ,  $r = 1, \dots, R$ , taking the sample weights from the respective bootstrap samples into account.
3. Estimate the variance  $V(\hat{\tau})$  by the variance of the  $R$  bootstrap replicate estimates:

$$\hat{V}(\hat{\tau}) := \frac{1}{R-1} \sum_{r=1}^R \left( \hat{\tau}_r^* - \frac{1}{R} \sum_{s=1}^R \hat{\tau}_s^* \right)^2. \quad (24)$$

4. Estimate the confidence interval at confidence level  $1 - \alpha$  by one of the following methods (for details, see Davison and Hinkley 1997):

**Percentile method:**  $\left[ \hat{\tau}_{((R+1)\frac{\alpha}{2})}^*, \hat{\tau}_{((R+1)(1-\frac{\alpha}{2}))}^* \right]$ , as suggested by Efron and Tibshirani (1993).

**Normal approximation:**  $\hat{\tau} \pm z_{1-\frac{\alpha}{2}} \cdot \hat{V}(\hat{\tau})^{1/2}$  with  $z_{1-\frac{\alpha}{2}} = \Phi^{-1}(1 - \frac{\alpha}{2})$ .

**Basic bootstrap method:**  $\left[ 2\hat{\tau} - \hat{\tau}_{((R+1)(1-\frac{\alpha}{2}))}^*, 2\hat{\tau} - \hat{\tau}_{((R+1)\frac{\alpha}{2})}^* \right]$ .

For the percentile and the basic bootstrap method,  $\hat{\tau}_{(1)}^* \leq \dots \leq \hat{\tau}_{(R)}^*$  denote the order statistics of the bootstrap replicate estimates.

With package **laeken**, variance estimates and confidence intervals can easily be included in the estimation of an indicator. It is only necessary to specify a few more arguments in the call to the function computing the indicator. The argument **var** is available to specify the type of

variance estimation, although only the bootstrap is currently implemented. Furthermore, the significance level  $\alpha$  for the confidence intervals can be supplied via the argument `alpha` (the default is to use `alpha=0.05` for 95% confidence intervals). Additional arguments are then passed to the underlying function for variance estimation.

```
R> arpr("eqIncome", weights = "rb050", design = "db040", cluster = "db030",
+      data = eusilc, var = "bootstrap", bootType = "naive",
+      seed = 1234)
```

Value:

```
[1] 14.44422
```

Variance:

```
[1] 0.220742
```

Confidence interval:

```
  lower  upper
13.64587 15.48150
```

Threshold:

```
[1] 10859.24
```

For the bootstrap, the function `bootVar()` is called internally for variance and confidence interval estimation. Important arguments are `design` and `cluster` for specifying the strata and clusters in the sampling design, `R` for supplying the number of bootstrap replicates, `bootType` for specifying the type of bootstrap estimator, and `ciType` for specifying the type of confidence interval. For reproducibility, the seed of the random number generator can be set via the argument `seed`.

An important feature of package **laeken** is that indicators can be estimated for different subdomains with a single command, which still holds for variance and confidence interval estimation. As for point estimation, only the `breakdown` argument needs to be specified (cf. the example in Section 4.2).

## 6.2. Calibrated bootstrap

In practice, the initial sample weights from the sampling design are often adjusted by calibration, for instance to account for non-response or to ensure that the sums of the sample weights for all observations within certain subgroups equal the respective known population sizes. However, drawing a bootstrap sample then has the effect that the sample weights in the bootstrap sample no longer sum up to the correct values. As a remedy, the sample weights of each bootstrap sample should be recalibrated. For better accuracy at a higher computational cost, the *calibrated bootstrap* algorithm extends the naive bootstrap algorithm from the previous section by adding the following step between Steps 1 and 2:

- 1b. Calibrate the sample weights for each bootstrap sample  $\mathbf{X}_r^*$ ,  $r = 1, \dots, R$  (see, e.g., [Deville and Särndal 1992](#); [Deville et al. 1993](#), for details on calibration).

Using **laeken**, the function call for including variance and confidence intervals via the calibrated bootstrap is very similar to its counterpart for the naive bootstrap. A matrix of auxiliary calibration variables needs to be supplied via the argument **X**. The function `calibVars()` can thereby be used to transform a factor into a matrix of binary variables. In the example below, information on region and gender is used for calibration. Furthermore, the argument **totals** can be used to supply the corresponding population totals. If the **totals** argument is omitted, the population totals are computed from the sample weights of the original sample. This follows the assumption that those weights are already calibrated on the supplied auxiliary variables.

```
R> aux <- cbind(calibVars(eusilc$db040), calibVars(eusilc$rb090))
R> arpr("eqIncome", weights = "rb050", design = "db040", cluster = "db030",
+       data = eusilc, var = "bootstrap", X = aux, seed = 1234)
```

Value:

```
[1] 14.44422
```

Variance:

```
[1] 0.2236223
```

Confidence interval:

```
  lower  upper
13.66096 15.45736
```

Threshold:

```
[1] 10859.24
```

## 7. Conclusions

In this paper, we demonstrate the use of the R package **laeken** for computing point and variance estimates of indicators from complex surveys. Various commonly used indicators on social exclusion and poverty are thereby implemented. Their estimation is made easy with the package, as the corresponding functions allow to compute point and variance estimates with a single command, even for different subdomains of the data.

In addition, we illustrate with a simple example that some of the indicators are highly influenced by extreme outliers in the data (cf. [Hulliger and Schoch 2009](#); [Alfons \*et al.\* 2013b](#)). As a remedy, a general procedure for robust estimation of the indicators is implemented in **laeken**. The procedure is based on fitting a Pareto distribution to the upper tail of the data and has the advantage that it can be applied to any indicator. A diagnostic plot thereby allows to check whether the Pareto tail model is appropriate for the data at hand.

Concerning variance estimation, further techniques for complex survey samples are available in R through other packages. For instance, package **EVER** ([Zardetto 2012](#)) provides functionality for the delete-a-group jackknife. Other methods such as balanced repeated replication are implemented in package **survey** ([Lumley 2004, 2012](#)). The incorporation of those packages for additional variance estimation procedures is therefore considered for future work.

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