#### Master thesis



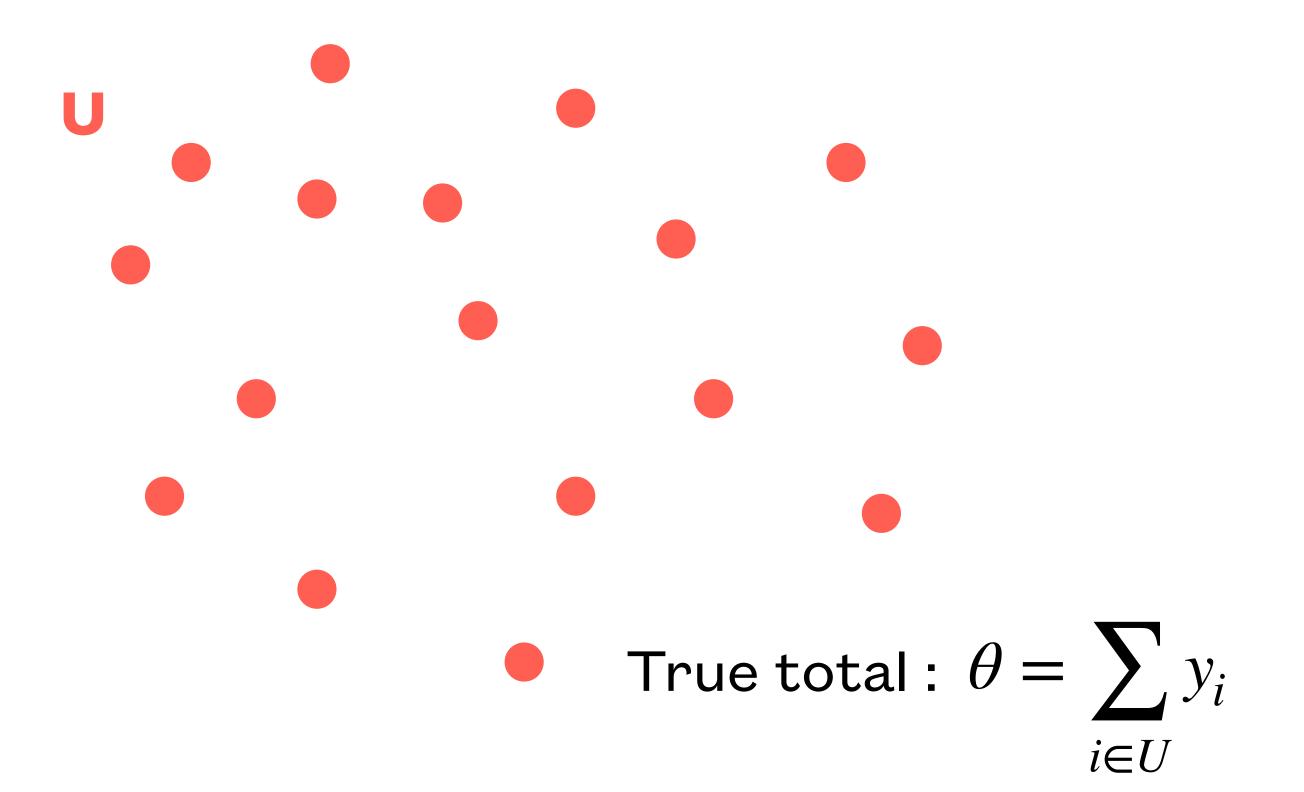


# Enhancements to the REVIVALS package

# Introduction

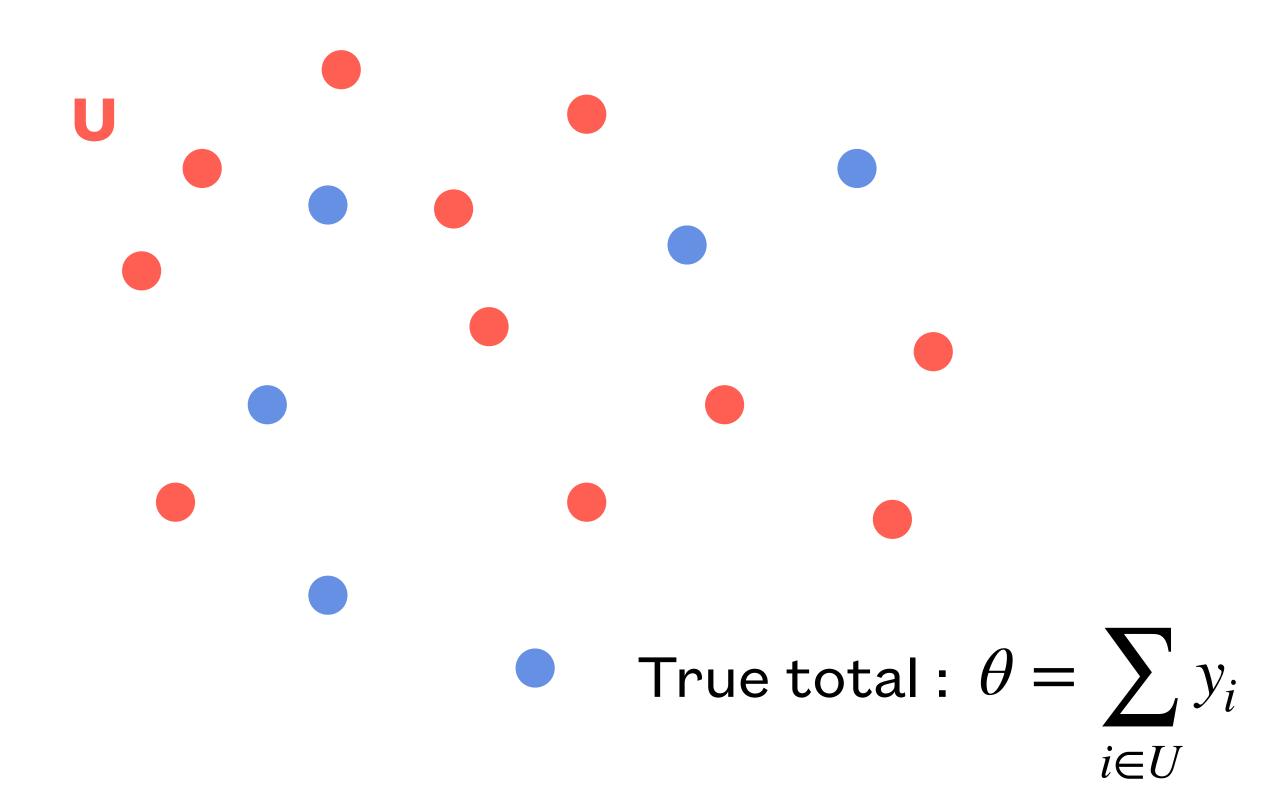
### Aim

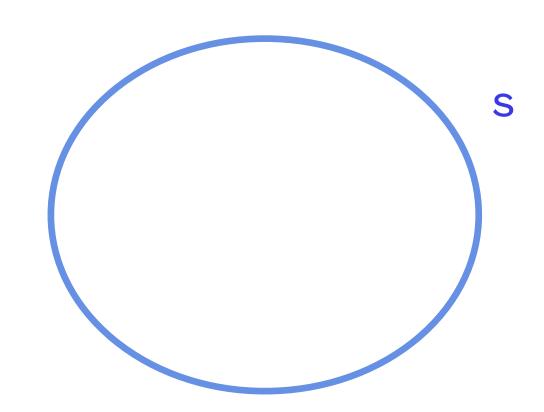
1. We are trying to estimate a total



### Aim

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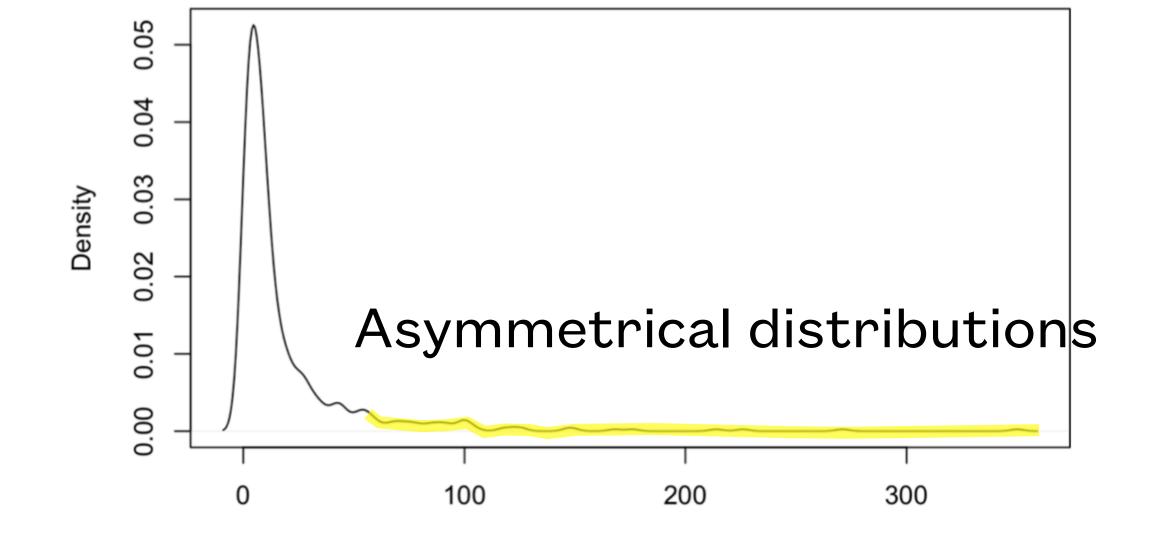


Horvitz-Thompson? 
$$\hat{\theta} = \sum_{i \in s} d_i y_i$$

### Aim

1. We are trying to estimate a total

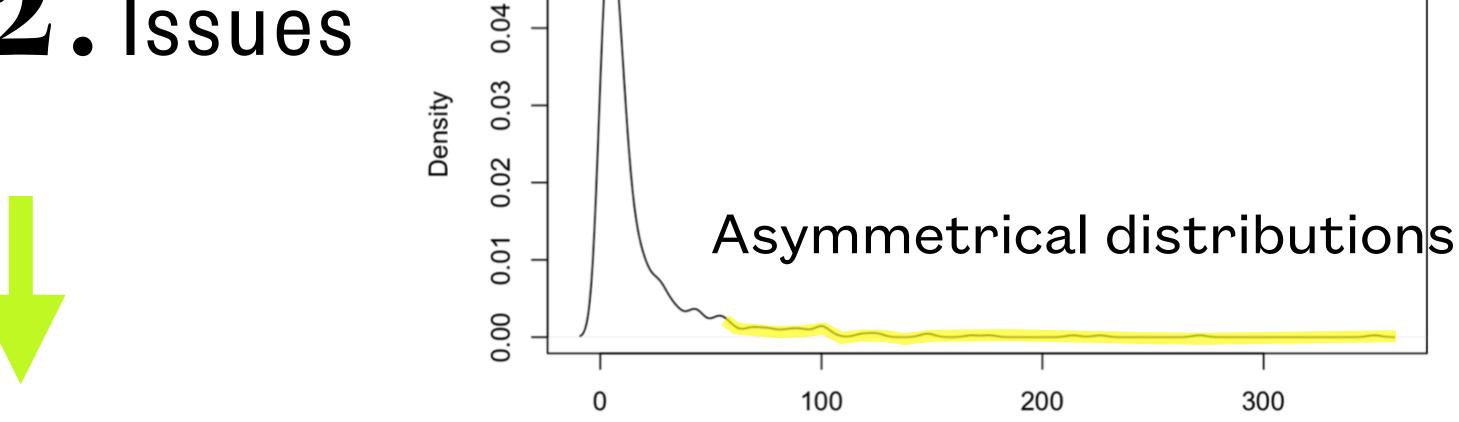
2. Issues



Editing stage has already been done

1. We are trying to estimate a total

2. Issues

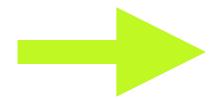


Editing stage has already been done

3. We need robust estimators

### Workdone

• Beaumont et. al. (2013) proposed to use the conditional bias (CB) as a measure of influence



Robust version of the Horvitz-Thompson estimator

• C. Favre-Martinoz started to build a package (revivals)

#### **GENERAL GOAL**

Enhancing the revivals package

### Workdone

1.

wrapper



1. Conditional Bias estimation

2. Robust HT estimation

3. Associated tuning constant

4. Robust estimator under winsorised form

2. Robustness enhancements

3. Article

#### SUMMARY

- Introduction
- Dissecting the revivals package
- Application with wrapper function

• Finite population of N units:  $U = \{1, ..., N\}$ 

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• Variable of interest:  $y_i$ ,  $\forall i \in U$ 

Finite population of N units:

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$$y_i$$
,  $\forall i \in U$ 

• Sample:

$$s = \begin{pmatrix} I_1, \, \dots, \, I_i, \, \dots, \, I_N \end{pmatrix}^T$$
 where  $I_i = \left\{ egin{array}{ll} 1 & ext{if } i \in s \\ 0 & ext{otherwise.} \end{array} 
ight.$ 

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• 1st-order inclusion probabilities:  $\pi_i = \mathbb{P}(i \in S)$ 

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Design weight:

$$d_i = \frac{1}{\pi_i}$$

Design	Description	$\pi_i$
si	We draw a sample of size $n$ with equiprobability among all possible samples.	$\frac{n}{N}$
poisson	We fix $\pi=(\pi_1,\pi_2,,\pi_N)$ and randomly draw each observation independently. The sample size is random	(fixed)
rejective	We fix $\pi = (\pi_1, \pi_2,, \pi_N)$ and follow a Poisson design, rejecting all samples until we obtain one of size $n$ .	(fixed)

Table 1: Non-stratified sampling designs used in REVIVALS

# Literature review Conditional bias

• For a parameter heta and an estimator  $\hat{ heta}$  (Moreno-Rebollo et al. - 1999):

$$B_i^{\hat{\theta}}(I_i=1) = \mathbb{E}(\hat{\theta}-\theta \mid I_i=1),$$

• In the case of the HT estimator of a total, it becomes:

$$B_i^{HT}(I_i = 1) = \sum_{j \in U} \left( \frac{\pi_{ij}}{\pi_i \pi_j} - 1 \right) y_j$$

**Notation**:  $B_i^{HT}(I_i = 1)$  will simply be denoted  $B_i^{HT}$ 

### Literature review Conditional bias

Revivals function HTcondbiasest

SI

Theoretical

$$B_i^{HT} = \frac{N}{N-1} \left(\frac{N}{n} - 1\right) (y_i - \bar{Y}_U), \ \forall i \in U, \qquad \text{where } \bar{Y}_U = \frac{1}{N} \sum_{i \in U} y_i$$

where 
$$\bar{Y}_U = \frac{1}{N} \sum_{i \in U} y_i$$

Estimated

$$\hat{B}_i^{HT} = \frac{n}{n-1} \left( \frac{N}{n} - 1 \right) (y_i - \bar{y}), \ \forall i \in U, \qquad \text{where } \bar{y} = \frac{1}{n} \sum_{i \in S} y_i$$

where 
$$\bar{y} = \frac{1}{n} \sum_{i \in S} y_i$$

Conditions to check: n > 1 / N is known

# Literature review Conditional bias

#### **POISSON**

Theoretical

$$B_i^{HT} = \left(\frac{1}{\pi_i} - 1\right) y_i$$

No need to estimate it

Revivals function
HTcondbiasest

# Literature review Robust estimator

Revivals function robustest

# How to use the conditional bias in order to obtain robust estimators in a design-based framework?

=> Robust Horvitz-Thompson (RHT) estimator (Beaumont et al. - 2013):

$$\hat{t}_{y}^{RHT} = \hat{t}_{y}^{HT} - \frac{1}{2} \left( \hat{B}_{min}^{HT} + \hat{B}_{max}^{HT} \right)$$

# Literature review Associated constant c

Revivals function tuningconst

#### General form

$$\hat{t}_y^{RHT} = \hat{t}_y^{HT} - \sum_{i \in S} \hat{B}_i^{HT} (I_i = 1) + \sum_{i \in S} \psi(\hat{B}_i^{HT} (I_i = 1))$$

where  $\psi$  is the Huber function, defined as:  $\psi(x) = \text{sign}(x) \times \min(|x|, c)$  where c > 0.

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#### Optimal constant c?

$$\min_{c} \max\{|\hat{B}_i^{RHT}(c)| i \in s\}$$

# Literature review Winsorised form

Revivals function robustweights

**Idea:** if 
$$d_i y_i > K$$
 then  $y_i \to \tilde{y}_i$ .

$$\rightarrow \hat{t} = \sum_{i \in S} d_i \tilde{y}_i$$

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# Literature review Winsorised form

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$$\rightarrow \hat{t} = \sum_{i \in S} d_i \tilde{y}_i \iff \hat{t} = \sum_{i \in S} \tilde{d}_i y_i$$

#### 2 winsorisation forms

Standard

$$\tilde{d}_{i}^{S} = d_{i} \frac{min\left(y_{i}, \frac{K}{d_{i}}\right)}{y_{i}}$$

Dalén-Tambay

$$\tilde{d}_i^{DT} = 1 + (d_i - 1) \frac{\min\left(y_i, \frac{K}{d_i}\right)}{y_i}$$

### Literature review Winsorisation constant

Revivals function
determinconstws
determinconstwDT

#### Optimal constant $K_{opt}$ ?

- We want:  $\hat{t}_y^{BHR} = \hat{t}_y^{std} = \hat{t}_y^{DT}$
- We know that:  $\hat{t}_y^{RHT} = \hat{t}_y^{HT} \frac{1}{2} \left( \hat{B}_{min}^{HT} + \hat{B}_{max}^{HT} \right)$
- Same form:  $\hat{t}_y^{HT} + \Delta(K)$

$$\min_{K} \max\{ |\hat{B}_{i}^{RHT}(K)| i \in s \}$$

$$\Leftrightarrow \Delta(K) = -\frac{1}{2} \left( \hat{B}_{min}^{HT} + \hat{B}_{max}^{HT} \right)$$

$$\Leftrightarrow \sum_{j \in s} a_j \max\left(0, d_j y_j - K\right) = \frac{\hat{B}_{min}^{HT} + \hat{B}_{max}^{HT}}{2}$$

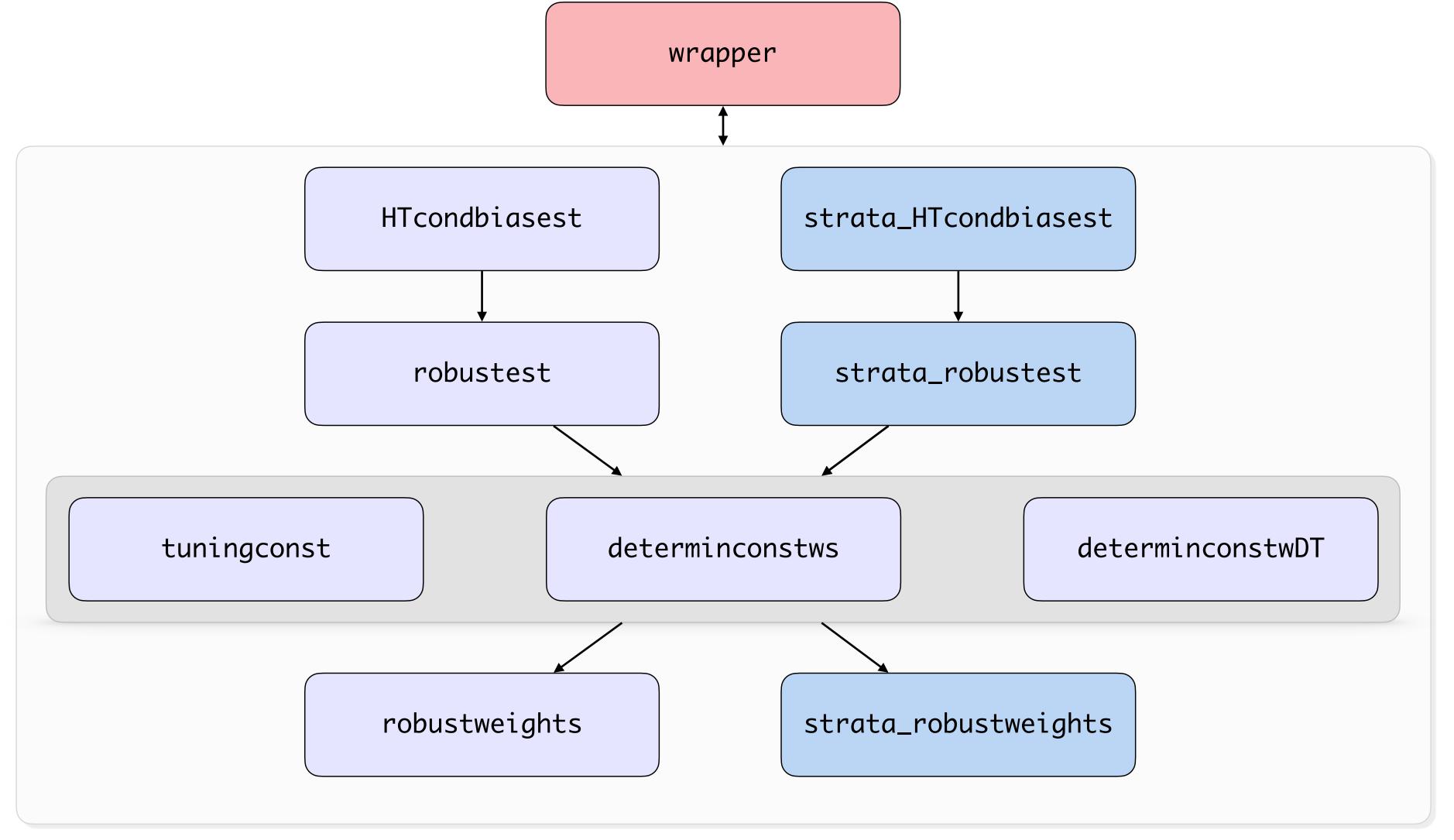
# Revivals Structure

1. Conditional Bias estimation

2. Robust HT estimation

3. Associated tuning / winsorisation constants

4. Robust weights computation



# Illustration with the wrapper function

# Illustration Data presentation

#### rec99htegne database:

- -N = 554 observations
- p=7 variables regarding the French communes in the Haute-Garonne department

	CODE_N	COMMUNE	BVQ_N	POPSDC99	LOG	LOGVAC	STRATLOG
1	31014	ARGUENOS	31020	57	94	1	1
2	31131	CAZAUNOUS	31020	47	56	4	1
3	31348	MONCAUP	31020	26	57	2	1
4	31447	RAZECUEILLE	31020	37	89	6	1
5	31140	CHEIN-DESSUS	31020	184	174	28	2

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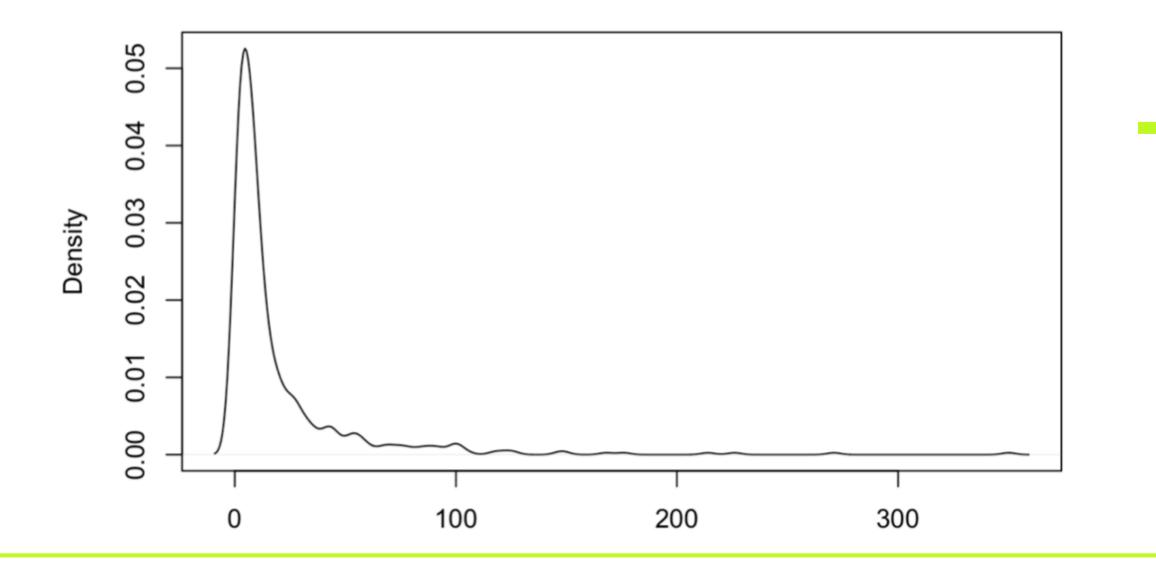
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### Illustration Data presentation

Basic descriptive statistics for LOGVAC

Min	Q1	Median	Mean	Q3	Max	$\mathbb{V}ar$	Kurtosis	Skewness
0.00	4.00	8.00	19.44	20.00	350.00	1104.50	29.450	4.533

LOGVAC density plot



any drawn sample will potentially contain some very influential values

• Sample size: n = 80 units

- Sample size: n = 80 units
- First order incl. probabilities

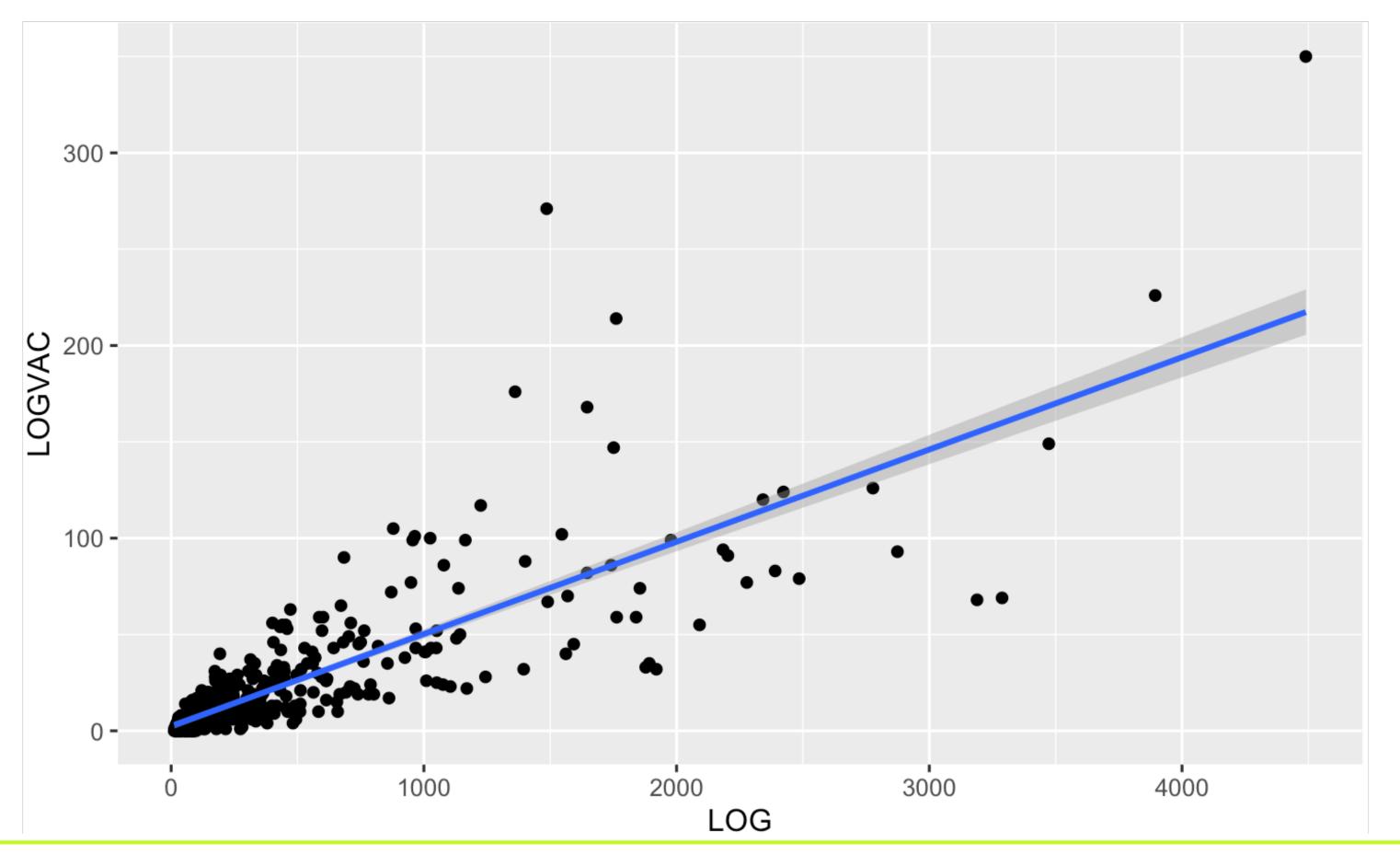
$$\pi_i = \frac{80}{554} \simeq 0.144$$

- Sample size: n = 80 units
- First order incl. probabilities

$$\pi_i = \frac{80}{554} \simeq 0.144$$

- Poisson and Rejective: use

use an auxiliary variable LOG



Linear relationship

Confirms the validity of LOG as an auxiliary variable.

•  $\rho(LOG, LOGVAC) \simeq 0.8189$ 

- Sample size: n = 80 units
- First order incl. probabilities

$$\pi_i = \frac{80}{554} \simeq 0.144$$

- Poisson and Rejective:

$$\pi_i = \frac{log_i \times n}{LOG} = \frac{log_i \times 80}{197314}$$

## Illustration Syntax

```
wrapper(data = ech,
        varname = c("LOGVAC"),
        gn = N,
        est_type = c("BHR", "standard", "DT"),
        method = "si",
        pii = ech$piks,
        id = "CODE_N")
```

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#### Illustration Summary tables

	est_type	var	RHT	tuning_const	HT	${ m rel\_diff}$	nb_modif_weights
1	BHR	LOGVAC	11776.00	642.00	12284.95	-4.14	1
2	standard	LOGVAC	11776.00	973.00	12284.95	-4.14	1
3	$\operatorname{DT}$	LOGVAC	11776.00	887.10	12284.95	-4.14	1

Table 5: Summary table for SRSWOR

	$\operatorname{est\_type}$	var	RHT	$tuning\_const$	HT	${ m rel\_diff}$	$nb\_modif\_weights$
1	BHR	LOGVAC	11174.90	239.78	11323.94	-1.32	5
2	standard	LOGVAC	11174.90	292.60	11323.94	-1.32	5
3	$\operatorname{DT}$	LOGVAC	11174.90	271.66	11323.94	-1.32	6

Table 6: Summary table for Poisson sampling

### Illustration Detailed tables

CODE_N	init_weight	LOGVAC	condbias LOGVAC	new_weights LOGVAC_BHR	modifed LOGVAC_BHR	new_weights LOGVAC_standard	modifed LOGVAC_standard	new_weights LOGVAC_DT	modifed LOGVAC_DT
31342	6.92	10.00	-73.05	6.92	FALSE	6.92	FALSE	6.92	FALSE
31020	6.92	90.00	406.95	6.92	<b>FALSE</b>	6.92	<b>FALSE</b>	6.92	<b>FALSE</b>
31086	6.92	5.00	-103.05	6.92	<b>FALSE</b>	6.92	<b>FALSE</b>	6.92	<b>FALSE</b>
31002	6.92	7.00	-91.05	6.92	<b>FALSE</b>	6.92	<b>FALSE</b>	6.92	<b>FALSE</b>
31264	6.92	11.00	-67.05	6.92	FALSE	6.92	FALSE	6.92	FALSE

**Table 7:** Detailed table for SRSWOR

CODE_N	init_weight	LOGVAC	condbias LOGVAC	new_weights LOGVAC_BHR	modifed LOGVAC_BHR	new_weights LOGVAC_standard	modifed LOGVAC_standard	new_weights LOGVAC_DT	modifed LOGVAC_DT
31342	15.81	10.00	148.12	15.81	FALSE	15.81	FALSE	15.81	FALSE
31083	19.60	16.00	297.64	15.99	TRUE	18.29	TRUE	17.11	TRUE
31027	34.37	4.00	133.50	34.37	<b>FALSE</b>	34.37	FALSE	34.37	<b>FALSE</b>
31052	4.21	20.00	64.26	4.21	FALSE	4.21	FALSE	4.21	FALSE

**Table 8:** Detailed table for Poisson sampling

#### Revivals Robustness - Warnings

- Notification that  $d_i$  is redundant and only  $\pi_i$  is being used ;
- For rejective sampling design, D must be large enough and N/D bounded;
- Message when the estimation method is wrongly specified or multiple methods are specified. In both cases the method is set to 'si' by default.
- Warning when one of the interest variables contains negative values: it could be that the  $\hat{B}^{HT}_{\min} + \hat{B}^{HT}_{\max}$  from the robust estimator equation  $\hat{t}^{RHT}_y = \hat{t}^{HT}_y \frac{1}{2} \left( \hat{B}^{HT}_{\min} + \hat{B}^{HT}_{\max} \right)$  is negative.

### Revivals Robustness - Stops

- We make sure that none of the interest variables contains any missing value;
- We stop the code when  $\pi_i$  (or  $d_i$ ) has a different number of rows than the data file;
- We check that  $\frac{1}{2}(\hat{B}_{min} + \hat{B}_{max}) \geq 0 \Leftrightarrow \hat{B}_{max} \geq -\hat{B}_{min}$ . Functions determinconsts and determinconstwDT giving the winsorisation constants do not work otherwise.

#### Conclusion

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